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AN ANALYSIS OF FACTORS THAT INFLUENCE LOGISTICS, OPERATIONAL AVAILABILITY, AND FLIGHT HOUR SUPPLY OF THE GERMAN ATTACK HELICOPTER FLEET

by

Manuel Loewer

June 2017

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The goal of this thesis is to identify factors that could lead to measurable improvement in operational availability and flight-hour supply of the German Army helicopter fleet. This research uses statistical analysis of failure-time data and a simulation model that emulates the usage and maintenance policies adopted by the fleet. The simulation model reflects normal daily operating and maintenance activities and manages individual aircraft with respect to flying operations and maintenance activities, including extensive scheduled inspections, non-recurring special inspections, and failure-driven unscheduled maintenance actions for each aircraft on a daily basis.

The model reproduces recent historical trends accurately. It provides useful insights about the future availability of the German Army helicopter fleet by keeping current policies in place and making investments in the maintenance system. Without such investments, availability can be expected to decline over the next several years. By increasing maintenance assets, the decline can be reduced in a quantifiable manner.

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LIST OF ACRONYMS AND ABBREVIATIONS

ADT	abstract data type
AFG	Afghanistan
AHRgt	attack helicopter regiment
AIC	Akaike Information Criterion
ASGARD	Afghanistan Stabilization German Army Rapid Deployment
COC	certificate of conformity
CSV	comma-separated values
DES	discrete-event simulation
DSK	German: Division Schnelle Kraefte) (English: Division Rapid Reaction Forces
FH	Flight Hours
FIFO	first-in-first-out queuing technique
HOT	French: Haut Subsonique Optiquement Teleguide (English: High subsonic optical wire-guided missile)
IPT	Integrated Planning Team
ISAF	International Security Assistance Force
LIFO	last-in-first-out queuing technique
MBB	Messerschmidt Bölkow-Blohm
MOE	measure of effectiveness
MTBF	mean time between failures
NOB	nearly orthogonal balanced design
NOLH	nearly orthogonal Latin hypercube
OSIRIS	Optical Stabilized InfraRed Integrated System
PAH	German: Panzerabwehrhubschrauber (English: anti-tank helicopter)
PARS 3 LR	see TRIGAT
QQ-plot	Quantile-Quantile plot
SASPF	Standard Application Software Product Family by SAP
TBF	Time Between Failure
TCI	time critical item

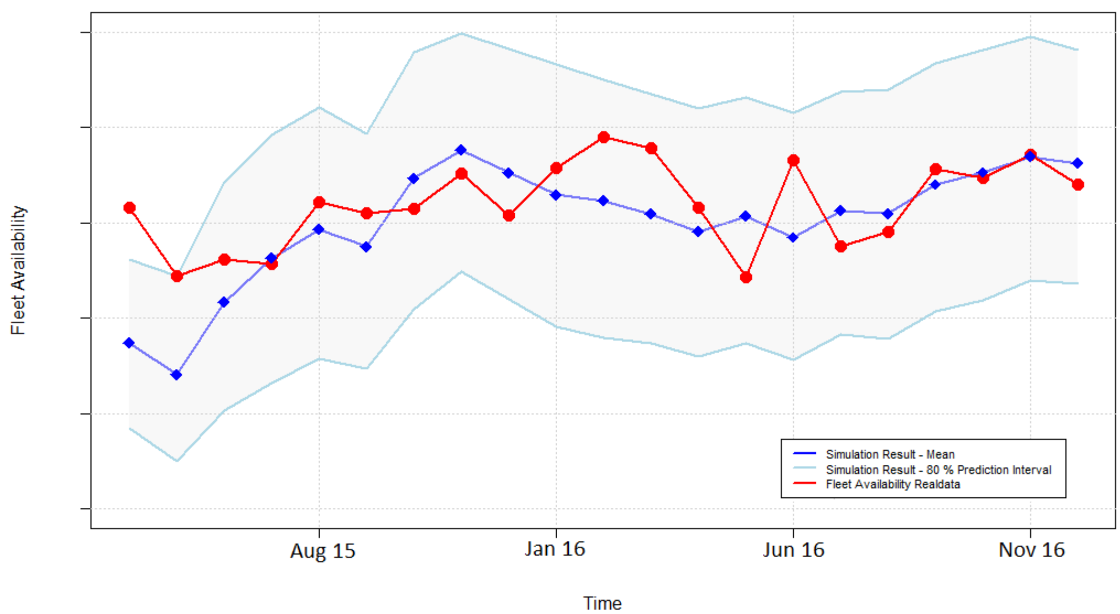
TRIGAT	Third generation anti-tank long-range missile
UH	German: Unterstuetzungshubschrauber (English: support helicopter)
YFP	yearly flight program

EXECUTIVE SUMMARY

From the beginning of the procurement phase accompanying the transition to the UH TIGER multi-role attack helicopter in 2005, the availability of the German Army aircraft fleet has been undermined by a complex mix of logistical challenges. In this thesis, we present a simulation model that can be exercised to examine the effects of a set of policy changes that have been proposed to improve availability of the TIGER fleet. The simulation model incorporates several factors that are known to affect availability, including those that address maintenance policy and reliability. By applying the model to fleet data, the model response can be used to predict the impact of changes in these factors on fleet availability, flight hour supply, mission accomplishment, and utilization of maintenance capacity.

Visual displays of the results of exercising the model convey useful insights to support management decisions. Each measure of effectiveness can be evaluated as a function of the input factors or as a function of time. The model has a generic architecture, which makes it easy to adapt to changing fleet dynamics or to different aircraft types. Simulation input values may be derived from actual fleet data or specified by probability distributions. Simulation output can be tailored to the needs of the user, either generated by using designed experiments and then fit with sophisticated metamodels, or provided as a single time series output for a scenario of interest.

Data analysis plays an important role in shaping the simulation model. Data on aircraft failure times obtained from the TIGER fleet over a three-year period is used to estimate the parameters of Weibull probability distributions that are integrated into the simulation model. This allows the model to reflect the reliability characteristics of the fleet. In addition, data on maintenance times from the fleet are randomly resampled when running the model to enhance model realism. The use of a simulation model to represent the behavior of the system under theoretical scenarios invites skepticism unless it is shown that the model can reproduce known behavior of the system under applicable conditions. Demonstrating that the model captures realism in the system under investigation is known as validation. By implementing a rule set that describes the current fleet, including flight safety standards, and by using live fleet data, we validate our simulation model by comparing its output to conditions in the fleet that existed during the period April 2015 through December 2016. Focusing on the rate of availability of aircraft, we show that the mean deviation of the model output from actual availability during this period is approximately 4.3%. Figure 1 shows the model output relative to actual availability over time. The German Army accepted these results as sufficient to accredit the model for examining the response of the TIGER fleet to various policy options under consideration.



Validation result for MOE availability rate from period April 1, 2015-Dec. 31. 2016. For classification reasons, values on the y-axis are not presented.

Figure 1. Comparison of Simulated Outcome for Fleet Availability Rate with Historical Fleet Availability Data (ε = 4.3%)

By utilizing the final aircraft fleet model, we quantify the impact of each factor on fleet performance using appropriate measures of effectiveness, which we use to formulate recommendations for fleet management with reference to the current status of the TIGER fleet, which we define as the base case. Several alternate maintenance policies are evaluated at different levels of yearly fleet utilization. Although improvement in fleet availability and flight-hour supply could be achieved by improving any of the factors under consideration (decreasing inspection duration, increasing maintenance assets, or increasing mean time between failure), any such improvement carries costs. For this reason, we evaluate improvement scenarios chosen in consultation with the German Army, which represent goals that the sponsor views as useful for consideration.

At the current utilization level of 80 flight hours per aircraft per year, a 60% reduction in inspection time coupled with a 25% increase in maintenance assets would produce broad improvement in availability and flight supply but would not meet the mission-completion goal or reverse a declining trend in availability after achieving a maximum several years into the future. We assume that reduction in inspection duration could be achieved without reducing the quality of inspections. In any scenario, meeting the mission-completion goal could be achieved only with a substantial improvement in aircraft reliability, which is a concerning but important insight. Furthermore, in each of the scenarios considered, availability would decline after achieving a maximum value several years into the future, although the decline would be less in scenarios that imply the greatest level of improvement in inspection duration, maintenance assets, or reliability. At higher levels of fleet utilization, such as 120 flight hours per year per aircraft, improvement in reliability is a practical necessity to achieve sustainable fleet performance.

Common features of all recommendations are that the inspection duration should be reduced by at least 60% while simultaneously increasing maintenance capacity by at least 25% to achieve a sustainable fleet performance at a satisfactory level.

An analysis approach using simulation to gain insight about the systemic behavior of an aircraft fleet has never been attempted within the German Army aviation forces before. Having an analysis tool that can be used on any standard computer to produce meaningful assistance for quick-turnaround management decision-making is a huge step forward, especially given the complexity of the aircraft and the guideline, procedural, and technology constraints that fleet managers must confront. The German Army now has the capability to make the most out of its operational fleet data. If maintained properly, the model’s flexible architecture is adaptable to any kind of system changes in the future, and can incorporate other flying weapon systems. This thesis explores uncharted waters and should be considered as a guide for future analysis projects and further tool development to support fleet management.

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This thesis is dedicated to my wife, Jessica, and my daughter, Lydia, who are the reasons why I came to Naval Postgraduate School. They supported me above all expectations while waiting patiently for me to wrap up each workday. Without them, this study, which could become an important management decision tool for the German Army, would never have happened.

This work is meant to support all the hardworking women and men of the TIGER community who are responsible for servicing the aircraft around daily flight operations at home and abroad as well as fleet management personnel who work very hard to improve fleet performance.

While I was posted in Attack Helicopter Regiment 36 in Fritzlar, Germany, among those specialists I was able to make contributions to solve problems that came along with the transition process to a new weapon system. Later, during my time in the logistics department of the DSK, I had deeper insights into the story the operational data told and the challenges that appeared on a daily basis. Without having the capability and the time to look deeper into the problems, I knew that there was more to derive from the given operational data than what we were able to comprehend at the time. With my deployment to study Operations Research at NPS, I gained a new level of understanding through the mathematical and statistical techniques taught in the courses. This newly acquired expertise and NPS faculty support allowed me to reach out to my superiors in Germany with a study proposal. I found acceptance within the Department of In-Service Fleet Management for the TIGER, which also became the sponsor of this thesis.

Therefore, I would like to thank LTC Lehmann and his team for believing in the capabilities of new statistical methodologies and providing incredible support during the course of my research. In addition, I would like to thank my advisors, Professor Koyak and Professor Sanchez, for their professional guidance and patience as I worked through this rich material. I am grateful to all these wonderful people who helped make this work possible.

I. INTRODUCTION

A. CHALLENGES

Since 2005, the German Army has operated a fleet of a new attack helicopter type, called UH TIGER. Even today, after the initial evaluation phase of pre-series models ended four years ago and the fleet accomplished an 18-month deployment cycle in Afghanistan, the procurement process still is not finished. While aircraft availability is not easy to maintain with a small fleet in the early years of acquisition, with logistical supply processes still under development, the now aging fleet continues to lack sustainable availability. The major challenges to fleet management are a growing fleet size, long-lasting inspection turnaround times, maintenance policies under review, lack of availability of certain vital equipment and parts, and the system reliability, to name only a few. This thesis is dedicated to providing insight into the impact of some of these factors on fleet availability as well as flight hour supply, and contributing to the decision-making process by quantifying optimization potential. The results should be used as a foundation for a living product that can be adjusted and for future application.

B. SCOPE AND OBJECTIVE

1. Scope

The scope of this thesis is to develop and implement a simulation model that best maps the systematic behavior of the TIGER attack helicopter fleet regarding various factors, including phase maintenance inspection system, logistics, personnel, mission assignment, unscheduled maintenance, and inventory and maintenance policies.

Despite the level of detail defined in the work agreement, by the end of this study the simulation model will cover the aircraft fleet down to the level of the individual helicopter object. It includes their properties, derived by data analysis performed during the study, including daily flight-hour demand generation, scheduling of aircraft deliveries, daily flight assignment, failure generation, non-recurring special inspection event scheduling and implementation of various maintenance policies. The next logical step is to include higher fidelity into the model down to the level of the major subsystems called main equipment and specific critical spare parts with their corresponding individual properties, such as underlying inspection system, flying hours, required personnel and failure behavior. This will allow evaluation of many more factors and effects connected with specific defined key equipment of interest. Due to time constraints, further work will be required beyond this thesis. Once finished, the model is intended to serve as a tool to assist in the decision-making process in German Army Aviation. It is designed generically for adaptation to other helicopter types—specifically, for allocation of assets and evaluation of factors for further contract design.

2. Objective

The objectives of this study are as follows:

- The development and implementation of a simulation-based model for the German UH TIGER fleet that includes the factors that significantly influence operational availability of the fleet;
- The evaluation and quantification of the impact imposed by different maintenance policies, aircraft reliability, inspection duration and changes in maintenance capacity on fleet availability and flight hour supply (bank time) over time within an increasing fleet size based on the given data.

3. Basic Research Questions

- What factors drive the systematic behavior of the German UH TIGER fleet regarding operational availability and flight hour supply, and which mathematical descriptions best fit the evaluated behavior of these factors?
- How does the maintenance system respond to changing rates in demand of helicopters and flight hours for helicopter operations (fleet utilization) on a daily basis?

- How do inspection turnaround times and failure repair times influence operational availability?
- How do measures such as changes in maintenance capacity, allocation of personnel, and maintenance policies like inspection systems affect operational availability and bank time? Can these effects be quantified?
- How does availability of specific subsystems and spare parts influence operational availability?
- With respect to factors specified above, how can a fleet utilization of 120 flight hours per aircraft per year be instantiated on an 80% accomplishment level while simultaneously maintaining a daily availability of ten aircraft?
- How do resulting recommendations affect dock utilization?
- How can simulation optimization and data farming techniques be used to answer these questions robustly, given uncertainty in significant factors and system performance?

C. BACKGROUND

1. German Army Attack Helicopter Fleet

During the Cold War, Germany faced the imminent threat of possible military aggression imposed by the Warsaw Pact along the Iron Curtain. Possible scenarios included massive military strikes by heavy armored battle groups from the east. Therefore, the front line in West Germany was structured in combat zones from north to south with areas of responsibility for German and Allied troops (Figure 1). Later, during the Vietnam War in the 1960s and 1970s, attack helicopters became a popular force multiplier, allowing support for boots on the ground via close air support and air strikes, and providing air transport capabilities.

Iron Curtain with anticipated NATO/Warsaw Pact force structures and German anti-tank regiment locations during the Cold War. Highlighted locations are as follows: (1) Hohenlockstedt, (2) Celle, (3) Fritzlar, and (4) Roth.

Figure 1. NATO Forward Strategy—Central Region in the 1980s. Adapted from Kuersener. (2013).

In the late 1970s, to strengthen the front line in Europe the German Army was equipped with BO-105 anti-tank helicopters, which could carry up to six HOT 3 wire-guided anti-tank missiles with a range of about 2.6 miles (Figure 2). Each wing of five helicopters was capable of taking out more than a complete armored company, without having any self-defense capability. Overall, three regiments with 60 helicopters each and a fourth mixed regiment were commissioned and maintained throughout the German-German border, as shown in Figure 1. According to Fiorenca (2016), in total, 312 BO-105 helicopters were taken into service in the German Army for anti-tank and transport purposes throughout the platform's life cycle.

Figure 2. MBB BO-105 PAH-1. Source: Hecker (2008).

While helicopters as a platform for air-to-ground combat and air defense systems became more mature and advanced, the BO-105 helicopter and its main weapon system soon became outdated. Hence, Germany and France started to develop a new anti-tank helicopter in cooperation with Aerospatiale and Messerschmitt-Bölkow-Blohm (MBB) in 1984. MBB emerged from Messerschmitt AG, Bölkow and the aviation division of Blohm+Voss. It was bought by Deutsche Aerospace AG (DASA) in 1989, which finally merged with Aerospatiale in 1992. The resulting company was formerly called Eurocopter Group and is now known as Airbus Helicopters (Gunston, 2005). The first prototype took off for its maiden flight on 27 April 1991. With the end of the Cold War (and, thus, the Warsaw Pact), the major threat has vanished. Out of area mission deployments (e.g., Kuwait in 1992 and the Balkan Wars during the 1990s) shaped the new defense reality, with new challenges and perspectives to military capabilities. During these years, the multi-role doctrine for new weapon systems became popular in Europe to face the new combat challenges and tight budgets. Hence, the specifications for the German anti-tank platform were modified to include armed battlefield reconnaissance, close air support, active and passive self-defense, and air escort capabilities. These major changes led to a significant increase in combat power and value, but also added additional constraints to the engineering processes, which induced major delays for the actual aircraft deliveries to the fleet. While the BO-105 started its third decade in service, the anti-tank helicopter regiments have been reduced from four to one due to severe budget cutbacks. Furthermore, Spain and Australia joined the TIGER community. In 2005, the first five UH TIGER Step 1 aircraft, one of five basic model type variants, were delivered to the German Army and deployed in LeLuc en Provence, France, to serve as pilot type-based flight training providers. The final phase of delivery started in August 2008 with the first fully mission-capable pre-series models, and ended in 2010 with the final-series Step 2 helicopters. These all were delivered to Attack Helicopter Regiment 36 in Fritzlar, Germany, which now is the last remaining attack helicopter regiment.

2. Attack Helicopter UH TIGER

The EC665, or Airbus Helicopter TIGER, (Figure 3) is a four-bladed, twin-engine multi-role attack helicopter with an airframe built from lightweight carbon-fiber composite materials and advanced avionic and optronic systems.

Figure 3. German Multi-role Attack Helicopter UH TIGER. Source: *Global Military Review* (2013).

It is capable of operating day and night and within a broad spectrum of weather conditions. Its gross weight at takeoff is about 6 tons and mission endurance without external tanks is up to three hours (McGowen, 2005). Nowadays, the system is used by four nations in four basic model types.

The model type used by the German Army is called the UH TIGER. This helicopter is able to carry five different weapon types in a single setup or weapon mix, suitable for different assignments like armed reconnaissance, air and ground escort, air-to-air combat, ground fire support, destruction, and anti-tank warfare. In addition, with the optional exterior fuel tank, a higher combat range or transition range can be achieved. The weapon mix includes HOT 3, PARS 3 LR anti-tank missiles, Hydra 70mm unguided rockets, a 12.7 mm GunPod and AIM-92 Stinger air-to-air missiles (Airbus Helicopters, 2015). Due to its design the TIGER's agility during flight, combined with its flat and narrow silhouette, low radar and infrared signature and passive CHAFF/FLARE weapon system, results in a significantly reduced vulnerability on the battlefield. Its survivability is further enhanced by ballistic protection in later versions, high crashworthiness, self-sealing tanks, and system architecture with designed-in redundancies and segregation. In addition, the UH TIGER has a mast-mounted sight, OSIRIS, which provides long-range target identification with a range over three miles and under-cover targeting capabilities. Overall, the UH TIGER is a state-of-the-art attack helicopter, which represents a major battlefield capability that significantly increases combat value and tactical flexibility in the modern joint combat environment and world-wide mission deployment. The German and the French systems have proven their combat readiness during missions in Afghanistan and Mali.

3. Fleet Development

The original plan was to procure 80 UH TIGERs, but budget constraints along with the end of the conscript system in the Bundeswehr forced the German government to restructure their Army and to close down one of the last two Attack Helicopter Regiments in Roth, Bavaria. This included a reduction of the total number of procured helicopters to 53. The system itself went through a development process, which included the German Army in the final phase to provide on-the-job training for pilots and maintainers as well as increase reliability by using company and military experience during mission readiness evaluation. This was a process with no precedent, other than the transport helicopter NH-90 project at that time. It revealed lots of infant mortality issues and warranty cases, and put pressure on the relationship between Airbus Helicopters and the German Army. To increase delivery speed and meet the demand for the ISAF mission in Afghanistan, aircraft were delivered in several development steps and model variants from 2005 to the present, which still influences fleet dynamics and in fact is one of the big challenges of this study. Currently in its retirement phase, the first model (only capable of performing in-flight and maintenance training) was the Step 1 model delivered in 2005. Still in service today and due for retrofit is the PBL-002 variant, which was delivered between 2008 and 2010. It was the first to allow shooting and therefore made pilot combat training possible. After 2010, the final series helicopter Step 2 models were delivered but soon had to be changed in design to be mission ready for the Afghanistan deployment between February 2013 and summer 2014. Henceforth, aircraft were delivered with an additional fourth radio for international ground troop communications, ballistic protection for the pilot, and additional equipment like sand filters and onboard video recording technology. These were the Step 2 G-Com, Afghanistan Stabilization German Army Rapid Deployment (ASGARD) F and ASGARD T models of the German UH TIGER helicopter variants. These different models essentially have the same capabilities, with some important exceptions like operability in sandy and hostile environments. Therefore, some of the helicopters are preferred, even demanded, over others. Also, the delivery process is long lasting and dependent on many factors. The timing of deliveries reflects production schedules intended to achieve high manufacturing productivity and to make sustainable fleet management easier in terms of consistent aircraft and maintenance facility utilization. In summary, the German Attack Helicopter Fleet (henceforth referred to as the “fleet”) is not homogeneous and is still growing in numbers.

The time frame of this thesis covers an open-ended interval starting on April 1, 2015. Hence, the fleet includes all individual aircraft currently in the fleet at that point in time, excluding aircraft already in retirement phase due to their pre-series equipment status. Due to classification purposes this thesis will refer to individual aircraft by an anonymous integer rather than using their real tail number. Starting with 27 aircraft, the delivery dates implemented into the simulation model are mapped to the individual Certificate of Conformity (CoC) Dates, which mark the legal hand-over date on which the aircraft were turned over by Airbus Helicopters to the German Army. During that period data access is frozen, aircraft data is migrated into the automated management system SAP Standard Product Family (SASPF), and the usage clock starts to run with the amount of the current flight hours reported. In total, the simulation model handles delivery of 26 new aircraft from production to the fleet in a five-year period, while producing accurate outputs under the assumptions described in Chapter II. This results in a total of 53 aircraft as the end-state of fleet size as it is defined by management today. Ultimately, management plans to retrofit all aircraft to the ASGARD model over time, to ensure consistent operational capability across the fleet. This will influence fleet dynamics in the near future, but will not be covered by this study. This might be considered in future work described in Chapter V.

Despite the enormous procurement and life cycle cost of the new TIGER helicopter fleet of the German Army, operational availability continues to lag operational requirements. In the scope of a ministerial task force, a comprehensive catalog of measures has been applied to the system. Among these, optimization of availability of time-critical items (TCI) and spare parts has shown positive results, which now must be carefully evaluated.

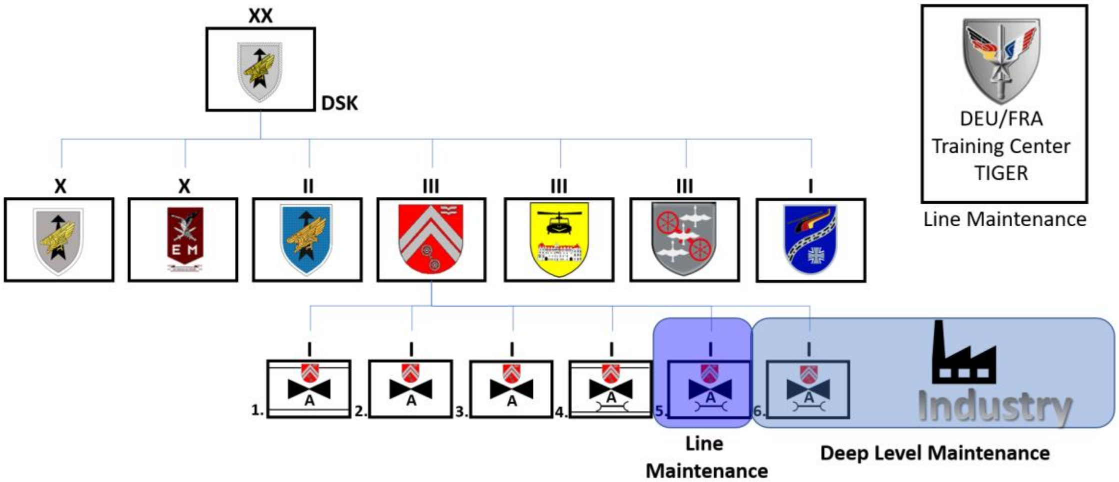
4. Fleet Management

The logistical and maintenance systems of flying weapon systems in the Bundeswehr, especially in the rollout phase with incomplete procurement as well as on-going development, follow a highly complex landscape of guidelines and procedures that operate under a broad spectrum of driving factors. First of all, and most importantly, flight safety guidelines have to be maintained. These are rules with a wider range and are far more rigid than guidelines for any ground-based system. They are the anchor for every operating and maintenance action as well as for logistical procedures. Each helicopter as an individual element is a complex system containing five different subsystems: airframe, electronics, avionics, structure, and weaponry. From a technical standpoint, it has a lot of unique properties besides its model type, such as mission status, failure behavior (reliability), and equipment status. Also, operational limitations may be applicable. Built-in equipment, spare parts, ground support equipment, material connected to the aircraft in general, and personnel have to be certified for use and work in and around the aircraft. Every spare part exchange from main equipment, engines or main gear boxes—down to each nut and bolt—has to be reported and documented in a proper way. There even exists a life-cycle file for each aircraft to store all reports and management forms from the first flight to decommissioning, in addition to the computer-based SASPF management system. For most maintenance actions, a so-called "six-eye" procedure has to be applied, meaning the work has to be performed by the mechanic, observed by a maintenance crew chief, and inspected by quality assurance personnel before the aircraft is allowed to be assigned for flight missions again. The flow of maintenance actions across an aircraft's lifetime consists of unscheduled maintenance due to failures, non-recurring special inspections, and mandatory scheduled maintenance procedures following a detailed two-dimensional (usage- and calendar-based) maintenance policy: the inspection system. Even some of the subsystems or main equipment like the engines have an additional inspection system, and therefore maintenance intervals of their own, which dictate when maintenance actions are due, and which also reduce availability of the aircraft. In addition, technical orders from the manufacturer (Airbus Helicopters) or the Army's in-service fleet management might pop up any time and cause downtime of single aircraft or the whole fleet due to immediate maintenance actions resulting from some fleetwide observed technical event. In addition to maintenance policies, there are other logistical factors and dependencies that also influence fleet performance, such as availability of spare parts, material, certified specialists, and valid regulations.

Fleet management must navigate through rough waters in order to meet all requirements and flight safety standards and still provide a high operational readiness level of the fleet. As an indicator of fleet-performance, operational availability rate—which is the proportion of aircraft in the fleet ready for flight assignment each day—represents the major measure of effectiveness besides flight hour supply (bank time). Flight hour supply is defined as the sum of each aircraft's number of flight hours until next scheduled major maintenance inspection. Also, the percentage of fulfilled flight hour demand per year is of interest to the sponsor. Therefore, these figures or some derivatives of them are used as response variables in modeling and are described in depth in Chapter III.

5. Organization of TIGER Aviation Maintenance

The German Army has grouped aviation capabilities in the Division Rapid Reaction Forces (DSK) located in Stadtallendorf, Germany. The primary home of the UH TIGER attack helicopter is Attack Helicopter Regiment 36 – Kurhessen located in Fritzlar. Moreover, Germany has the German/French training facilities in LeLuc en Provence, France and Fassberg, Germany. Figure 4 provides an overview of the structure. The maintenance organization in the German Army has three major parts: staff and supply, line maintenance, and deep level phase maintenance. All these elements are combined in Regiment 36 for TIGER aircraft maintenance. Additional external components are the Department of TIGER Capability Development and Department of In-Service Operational System and Supply Management, which is the sponsor of this thesis.



DSK consists of the following organizational entities (from left to right): (1) 1st Airmobile Brigade, Saarlouis (Germany), (2) 11th Airmobile Brigade, Schaarsbergen (Netherlands), (3) German Army Special Forces, Calw (Germany), (4) Attack Helicopter Regiment 36, Fritzlar (Germany), (5) Transport Helicopter Regiment 10, Fassberg (Germany), (6) Transport Helicopter Regiment 30, Niederstetten (Germany) and (7) System Center of Excellence TIGER in Ottobrunn (Germany)

Figure 4. Force Structure, Including Maintenance Units

Line maintenance for daily flight operations is conducted by the line maintenance units and spans maintenance tasks like pre-, turnaround, and post-flight inspections, failure repair, aircraft configuration changes, minor usage-based interval inspections, and special inspections up to a certain level of detail. Deep level phase maintenance (major overhaul or major inspections) contains a large number of maintenance actions and occurs according to the underlying aircraft inspection system on a calendar and usage interval basis. It is an intense procedure with a high degree of disassembly of main equipment groups and spare parts, with visual inspections to a high degree of detail. These procedures require special equipment, tools, and infrastructure called aircraft docks, as well as specialized equipment overhaul shops. Deep level maintenance capability is performed only by the heavy maintenance unit in AHRgt 36 with a certain capacity of aircraft docks and potentially additional capacity provided on a contract basis by industry. Therefore, aircraft due for deep level maintenance at the training facility have to be transferred for large-scale inspections.

D. LITERATURE REVIEW

1. Model Architecture

With reference to Lucas et al. (2015), simulation as methodology for systems analysis has gained significance within the scientific community throughout the last decades due to dramatically advanced computing hardware, simulation modeling paradigms, simulation software, and design-and-analysis methods. The authors claim: “When applied properly, simulation can provide fully as much insight, with as much precision as desired, as can exact analytical methods that are based on more restrictive assumptions” (p. 1, abstract). Furthermore: “The fundamental advantage of simulation is that it can tolerate far less restrictive modeling assumptions, leading to an underlying model that is more reflective of reality and thus more valid, leading to better decisions” (p. 1, abstract). In a variety of complex problems, like an aircraft fleet analysis, cost and long-term impact on fleet performance that make use of live experiments often infeasible for study purposes. Hence, simulation is often the only path to gain insight into a problem with manageable costs and almost no risk of collateral damage.

After finalizing the problem definition with the sponsor, we chose simulation as our method due to the complexity of the problem and inherent uncertainty of factors. The central subject of this study became building a simulation analysis tool for the German TIGER aircraft fleet as the underlying system of interest in order to analyze important factors that drive fleet dynamics from a maintenance-focused perspective. The major metric of interest is operational availability of the aircraft fleet as determined by the factors discussed earlier. During the literature review, I came across several approaches to similar research topics regarding availability of an aircraft fleet. For example, Mattila, Virtanen and Ravio (2008) made contributions to improved fleet management decisions in the Finnish Air Force by using an Arena Discrete-Event-Simulation (DES) model for quantifying fleet availability during peacetime and combat situations. Marlow and Novak (2013) used a MATLAB-based DES model to determine fleet size of Australian naval combat helicopters for land-based training and naval deployment cycles. Rais (2016) looked at personnel requirements for the Malaysian Army's new utility helicopter fleet using a DES model implemented in Simio. The common element of all these approaches was discrete-event simulation, which Law (2013) describes as the "model of a system that evolves over time by a representation in which the state variables change instantaneously at separate points in time" (p. 6, section 1.3). The major properties of all these models can best be summarized as discrete, dynamic and stochastic. With respect to the given study examples, it was obvious to consider DES as the methodology of choice. Since the operational utilization of an aircraft fleet is conducted on a calendar-driven basis, including various factors influenced by uncertainty that drive fleet condition over time, DES in fact turned out to serve well for the purpose of this study. As a last reference with respect to methodology, I would like to mention a second simulation study in collaboration with industry that is currently being established by the sponsor, although there are no publications or usable results yet. The focus of this study is the inventory policies for spare parts and components, and it should shed light on the impact of delivery lead times and inventory policies and development over time.

Although the cited studies have used the same modeling approach to solve similar problems, there are differences in the very nature of these problems in comparison to ours that are significant enough to distinguish between them. Another common element of previous studies is that one of the underlying major assumptions was homogeneity throughout the modeled fleet, consisting of aircraft entities that share the same input parameters and hence obey the same rules of behavior by using common parametric distributions when generating stochastic behavior. Although I did not know if these effects were negligible for the simulation at this point, from my own experience in practice I assumed there were significant differences between the individual aircraft in terms of aircraft failure behavior and other characteristics. This was supported by the actual failure data, which exhibited huge differences regarding the number of failures for different aircraft over the same time span. Therefore, I agreed with subject-matter experts from the sponsor's department to model individual aircraft objects rather than a homogeneous fleet.

In addition, three other major differences stand out in comparison to previous work in modeling methodology.

1. Because of aircraft deliveries and retirement of pre-series models, fleet size over time was not constant.

2. Because interest was focused especially on modeling the near-future timeframe, the fixed fleet state at $\mathbf{t_0}$ given by fleet data defined the starting point for the simulated time horizon. Hence, this was not a steady-state evaluation with a specific warm-up period. All simulated outcomes were important for both the analysis and the validation process

3. Because non-recurring special events such as technical orders from the manufacturer or government ("service bulletins"), TCI changes, hard landings, over-torque, or extraordinary maintenance events like equipment issues and warranty related cases were not included in prior studies referenced above, their impact on availability was not covered.

These events and their processing times are not easily modeled with parametric distributions, but they all are assumed to have a fair amount of impact on fleet dynamics. An urgent technical order ("TIGER safety warning"), for example, could down the whole fleet until measures have been applied, which could take several days.

As described above, the German TIGER Fleet is still very young. For the oldest aircraft in the fleet, we are looking at about seven years and an average of three years of usage. Also, deliveries are still introducing new aircraft to the fleet today, which will remain an ongoing process for the next two years. In addition, existing aircraft vary in model type. For standardization of capabilities there will be a retrofit procedure in the near future, which also comes into play. To be that flexible in modeling and to keep future study cost low, free software like *Python* (Python Software Foundation, 2010) and *R* (R Core Team, 2016) are used instead of 'commercial off the shelf' software products for further corporate use.

They are more than capable of doing the job. The model is supposed to be expandable with new features, which cannot be applied easily using Simio, for example, which is a powerful tool for modeling queueing systems but very limited when it comes to object entity variations, detail, and extraordinary event influences on the system. Therefore, the model was developed using the open source language *Python* 2.7 with its NumPy library by van der Walt, S., Colbert, S. C., & Varoquaux, G. (2011). *SimpleKit* by Oliver and Sanchez (2015) was utilized as the DES scheduling engine.

2. Data and Model Detail

Model detail is a very important aspect of building a simulation model. Law (2015) stressed this aspect a lot in his text. Detail is important for a realistic representation of system behavior, while having the proper strategy for a stepwise implementation and validation procedure is very important for tracking down erroneous behavior due to semantic errors. Too much detail sometimes does not add any substantial benefit, but potentially increases computational effort and cost. Often, implemented detail also requires specific data generated from the system of interest to produce valid results. Mattila, Virtanen and Ravio (2008) and Rais (2016) did not have much real fleet data for model implementation or did not include real fleet data at all, because it was highly classified. Therefore, they had to rely solely on subject-matter-expert opinion, which makes validation and accreditation a challenge.

Because of the excellent support by the sponsor, this study enjoys the ability to use real fleet data queried from SASPF and subject-matter-expert opinion to support an accurate model fit. Every two weeks, on average, phone conferences were held with a team in Germany for about two hours to discuss modeling options, data processing, and the interpretation of the information given by the data and results. In addition, a one-week business trip to Cologne for onsite correspondence and presentation of intermediate results facilitated interaction with the sponsor throughout the study. Although limitations regarding sharing content with advisors and publication of results applied due to classification, presentation of the generic model, the factor processing techniques, and some of anonymized fleet dependent results are feasible for this thesis. Because of the data supplied, the model is adjustable in detail to the needs of this project.

While the sources cited above stopped at the aircraft entity level, this model is expandable to the equipment and spare parts level by introducing equipment objects built into the aircraft object, with their own inspection systems, reliability parameters, and more properties. This was designated to be done in phase 2 of this project. Due to time constraints, this level of detail was not achieved in the thesis, but the interfaces and possibilities will be pointed out in the outlook presented in Chapter V. For example, Mattila, Virtanen and Ravio (2008) focused solely on the influence of maintenance policies on fleet availability regarding battle damage repair and scheduled maintenance in peacetime and combat situations, while in this study the maintenance system itself is the subject of evaluation with respect to a variety of input factors.

3. Simulation Design and Analysis

Law (2015) described outcomes of simulations as “estimates about system behavior, which if influenced by uncertainty often are driven by probability distributions” (p. 488, section 9.1). Furthermore, he stressed the fact that those results are derived from particular realizations of random variables that may have large variances. Hence, results derived by single simulation runs could differ greatly from the true characteristics of the corresponding model under review. To avoid erroneous inferences about the system under study, he pointed out the significant importance of input design techniques and mandatory replications for model inference. The problem described by this thesis spans several controllable decision variables, for example the number of aircraft docks or maintenance capacity, and maintenance policy options, to name a few. As another feature, the benefits of investments that improve reliability of the individual aircraft can be investigated by changing the MTBF parameters as model inputs. There is always more detail that can be implemented in the model, which results in a growing number of input factors but also yields the chance of getting more insight into fleet dynamics. Several implemented factors are discrete or categorical, like the number of aircraft docks or policy options. Some factors are continuous variables, like the number of flight hours per aircraft. All factors may have limits on values that are interesting to study. For example, a maintenance capacity of 50 aircraft docks, which is nearly as many as the number of aircraft in the fleet, is impractical and not worth evaluating.

The model is set up to facilitate either designed simulation experiments, or single-point excursions, by changing the values of some key model inputs. In addition, the simulation output resulting from changes in some factors could also be influenced by other factors. To cover these interactions and produce statistically meaningful output through simulation, a statistical response surface model, called a metamodel, of the simulation model's behavior is applied by utilizing a large nearly orthogonal-and-balanced design of input variables created by Vieira (2013). These designs contain different combinations for the input variables for each model iteration instead of simply replicating simulation runs at their mean values. In total, all input design points in the factor space built on these factor combination variations cover a significant proportion of the whole factor space. To save computational effort, enable coverage of nonlinearities and interactions, and ensure a nearly orthogonal coverage of the factor space, a nearly orthogonal-and-balanced version (NOB) design created by Vieira (2013) is used for the study (see Vieira et al. 2013 for more details about this type of design). Details regarding the specific factors and ranges for the simulation input design for this study can be found in Chapter II. In addition, several *Ruby* tools for automated execution of simulation model files with input handling through comma-separated value (CSV) files, comma extraction and error handling were used as a data farming wrapper for heavy duty simulation output processing (Sanchez, n.d.).

4. Data Analysis

Besides developing the simulation model, a fair amount of data analysis had to be done for factor and results analysis. The core tasks were a derivation of confidence intervals for input parameters, and modeling the aircraft failure behavior. As a side product, maximum likelihood estimation was used to derive Weibull survival functions for individual aircraft as described by Meeker and Escobar (1998).

A central element of data analysis was the modeling of aircraft failure behavior. Due to the vast number of applications regarding analysis of survivability data in recent decades of scientific work, two approaches were obvious to use for this purpose. (1) The exponential distribution is widely used for biological and medical survivability data, and (2) the Weibull distribution is used for product reliability of mechanical components. Nelson (1982) described the distribution developed by Waloddi Weibull in 1951 as useful in a great variety of applications, especially for evaluation of product life and strength of certain materials. For testing purposes both approaches were used throughout this study. In practice, the survival package in *R* by. Therneau (2017), especially the *survfit* and *survreg* functions, was used to produce analysis results. For achievement of a proper model fit, two methods were used to derive distribution parameters, which are described in the next chapter. In the Weibull case, maximum likelihood estimation described by both Meeker and Escobar (1998) and Nelson (1982) was utilized to fit shape and scale parameters for each aircraft.

Finally, simulation output data was analyzed with the linear regression analysis described by Faraway (2015, 2016). In practice, two *R* functions were utilized to produce results: the *lm* function by Ross Ihaka, which is based on Wilkinson and Rogers (1973), and the *predict* function. Logistic regression metamodels fit to the output of the experiment allow a wide spectrum of the response surface to be studied instead of focusing on one specific research question.

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II. METHODOLOGY

A. FRAMING THE PROBLEM

In the introduction given in Chapter I, the subject matter of this study has been sketched out briefly. This chapter is about how the problem has been approached, framed, and broken into actions before the actual coding phase began. These actions include the general modeling approach, scope of factor and model state-spaces, response and measure of effectiveness definition and, most importantly, the model assumptions made. Finally, the scope of data needed for modeling is outlined, as well as the specification of the model's input and output formats. These action packages also define the structure of this chapter. For simplification purposes this study focuses on basic peacetime flight operations. Special circumstances of deployment or combat are planned for the phase 3 extension-module in future work.

B. MODELING APPROACH

The aircraft fleet as the underlying system of interest is a collection of individual aircraft entities that are operated on a daily basis throughout the year. Each day flight operations like pilot training missions, exercises, or technical inspection flights are performed according to a weekly plan. Demand for helicopters and flight hours per operation follow a yearly flight plan, which is monitored and updated in meetings each day. Due to technical, logistical, and personnel fluctuations caused by maintenance issues, management decisions, or simply the chaotic implications of life, the actual demand is not deterministic. A properly scheduled flight, for example, can be canceled for many reasons, like a pilot's non-availability due to illness, an urgent technical order that downs the fleet, or a system failure without replacement, to name a few.

Aircraft operations require significant efforts in maintenance. Prior to each flight, sometimes in between flights, and after each flight, aircraft have to be inspected by specialists to ensure proper system operations. Often, failures occur that either require immediate attention prior to the next takeoff or allow for actions to be postponed to another time. Aircraft failure occurrence itself is stochastic in nature, which is very important for the model. The archetype UH TIGER achieves its operational readiness status and operational acceptance based on a variety of constraints. One of them is the underlying calendar- and usage-based inspection system, which forces operational planning into a certain time template, called the maintenance planning schedule. Although there is a general 10% tolerance for mandatory limitations on flight hours, this study assumes no tolerance. Maintenance procedures affect a number of factors which, in turn, affect turnaround time. Fluctuations in key personnel availability of maintenance units, availability of spare parts, or delays in performing maintenance can result in major delays with respect to turnaround time. The inspection task flow is defined by a centralized guideline system, which is inherently prone to delays. Hence, the failure repair times and inspection durations are stochastic. Additionally, occasional unexpected events happen, such as service bulletins from the manufacturer and government institutions, or in-flight events caused by pilot misconduct or emergencies. These occurrences require special maintenance tasks called non-recurring special inspections. Examples are bird strikes, hard landings, over-torques, main gearbox chip indications, or collateral impacts from extensive use of onboard weapons.

Among subject-matter experts, all these effects and events are considered important for a proper reflection of systemic behavior through model performance. Figure 5 summarizes all these basic aspects in a model-tasking overview, which indicates the amount of work to be performed in the modeling phase. Input information must be analyzed and formatted for model processing. The model layout itself contains necessary functionality capable of digesting and converting the input information into the desired output information. Finally, tools must be developed to analyze and prepare the output for suitable visualization to communicate the results achieved.

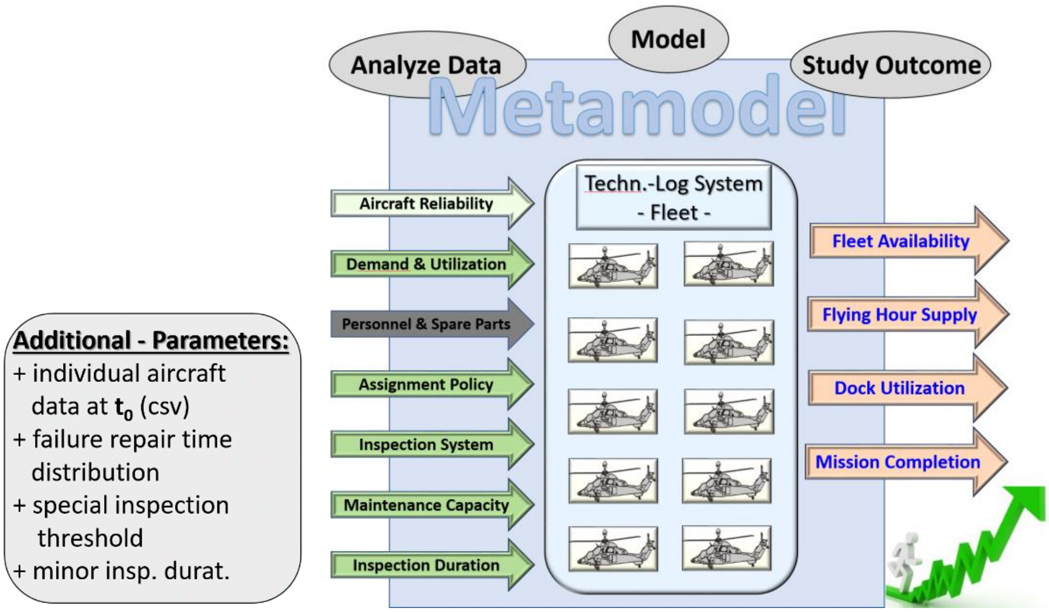


Figure 5. Model Input-to-Output Overview with Additional Parameters

These modeling implications require some form of time-based scheduling for daily flight operations, stochastic operational demand and aircraft failure generation, event-driven scheduling of maintenance actions, special tasks following from events like hard landing, etc. Each of these features requires information to be stored and manipulated through internal fleet data management. Fleet state at $\mathbf{t_0}$ must be properly defined and initialized, which requires input streaming capabilities due to the large volume of data. Law (2015, p. 6, section 1.3) classifies simulations with these properties as discrete-event. Other goals of the modeling framework are modularity, expandability, and adaptability to incorporate aircraft equipment, other aircraft types or machinery.

C. BASIC RULE HIERARCHY

We now discuss operational constraints and rule sets that are incorporated into the simulation model.

1. Flight Safety (Highest Priority)

Flight safety is the highest-priority constraint. It encompasses rules and requirements that always must be satisfied. Only serviceable aircraft are allowed to be assigned for flight operations. Aircraft with insufficient flight hour supply due to upcoming scheduled maintenance or critical failures must be discarded from the set of serviceable aircraft. The calendar- and usage-based age of each aircraft must be updated separately. Non-recurring special inspections due to extraordinary events must be performed before each takeoff.

2. Inspection System (High Priority)

Scheduled maintenance is based on guidelines of the underlying inspection system. Modeling the inspection system constraints accurately is important, as is recognizing a separation between minor flight hour inspections and major deep level inspections. Minor inspections are conducted after sufficient flight time is accumulated, although the time of the next major calendar-based inspection remains fixed. Deep-level maintenance inspections reset the calendar-based inspection clock. In cases concerning decoupled calendar-based and usage-based inspection systems, flight hours until next inspection is renewed only if an accumulated usage-based flight hour inspection is performed. In the case of calendar-based inspections, the usage clock is frozen at entry to the inspection.

Deep-level inspection durations are provided as a fixed input for each model run. This approach is chosen due to lack of data about the mandatory maintenance task network plan, personnel requirements, job performance times, and spare part availability. Data on minor usage-based inspections is available and used for modeling.

3. Aircraft Utilization (Medium Priority)

In practice, fleet management at the regimental level uses a heuristic to ensure even monthly utilization across the fleet. Each aircraft is assigned a monthly utilization budget, maintained on a weekly basis, derived from its flight hours to next inspection and the expected inspection closure time of aircraft currently utilizing a dock space. This procedure is an active measure used to minimize dock idle time and wait time for individual aircraft. This effect is depicted in Figure 6. Ideally, there should be a linear relationship between flight hours until next inspection across the fleet and the number of aircraft. Aircraft having the greatest remaining utilization budget are assigned higher priorities for flight mission selection.

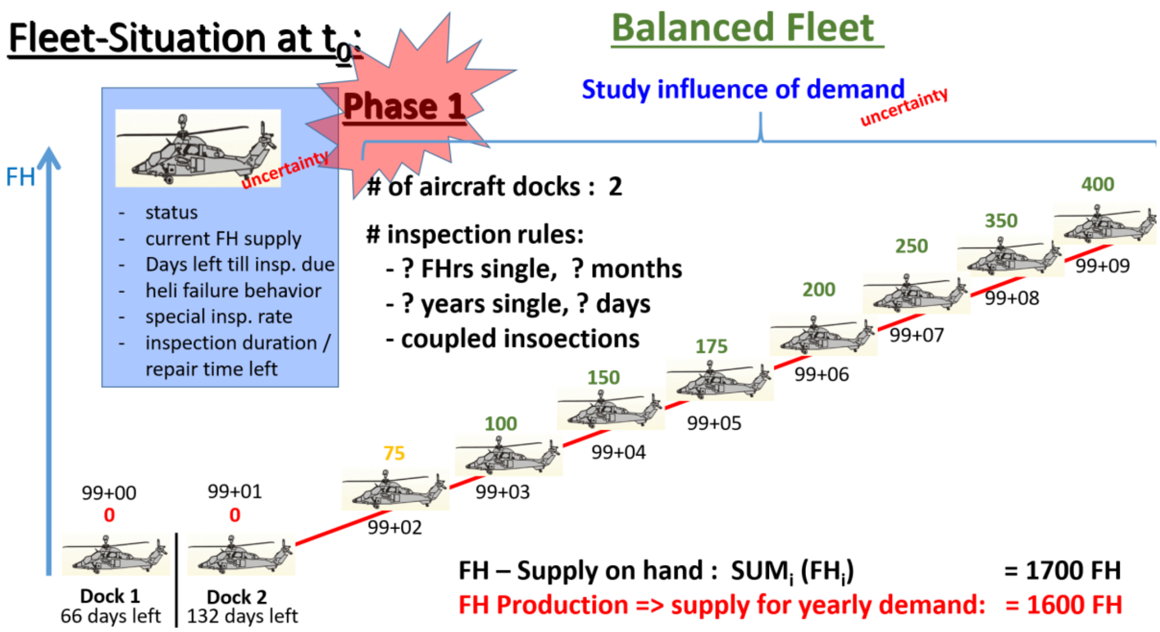


Figure 6. Fleet Balancing through Use of Monthly Utilization Budgets

4. Mission Completion Rate (Medium Priority)

The mission completion rate covers the proportion of flight hours actually used in the current fiscal year relative to the total demand generated in that year. If demand for flight hours exists on a specific day and serviceable aircraft are available, the demand will be satisfied even if there is only one aircraft, which will be assigned several times. In peacetime, an aircraft usually is not assigned more than four times a day. In recent years, the mission completion rate has fluctuated around 80%. Backed by the work agreement with the sponsor, 80% also will be determined as a threshold fleet-performance quality measure for the simulation model. In general, training missions are performed with one aircraft only. There are also squad- and wing-training exercises which include multiple aircraft. Mission scenario information is not available and will be ignored in the model.

Spare aircraft usually are kept mission ready in case of failures by other aircraft, but availability of spares is not guaranteed. The data does not contain information about the distribution and actual usage of spare availability. Given the lack of information, spares are omitted from modeling.

5. Dock Space Utilization (Medium Priority)

Because subject-matter experts have not observed long wait times and idle maintenance capacities so far, queuing techniques were not considered to be a major issue at the outset of this study. Fleet management historically has been successful using a monthly utilization budget approach because dock capacity has been adequate relative to fleet size. As fleet size grows we can expect this to change, possibly requiring new assignment policies. To facilitate analysis flexibility, the model tracks waiting queues and dock utilization as responses.

D. MODEL ASSUMPTIONS

All models are approximations of the actual system and we adopt assumptions to overcome the limitations of modeling. The assumptions made for this simulation model are defined in the following paragraphs.

1. General Assumptions

- Scheduling Timeline – For simplification purposes, this study reduces the time scheduling problem to workdays by assuming every month has 22 workdays; hence, every year has 264 workdays. Back-transformation of results to a calendar timeline is an easy conversion in Microsoft Excel or R.

- Annual Flight-Hour Demand per Aircraft – The average number of flight hours for each aircraft is the yearly flight plan divided by the annual average number of aircraft in the fleet, which is assumed to be the corresponding input parameter for demand computation.

- Flight-Hour Demand per Mission – The demand of flight hours per mission is a constant quantity for each flight on any given day.

- Seasonal Effects on Flight-Hour Demand – The demand for flight hours per month is constant across the year.

- Mission Completion – Aircraft fly 100% of the assigned hours, which is the demand of flight hours generated by the model, barring a failure. If failure occurs during a mission, aircraft utilization is determined by the failure time rather than the projected mission completion time since last failure, further referred to as partial flight hours (partial FH).

- Mission Status – The original 16 different mission statuses of an aircraft are reduced to the following:

  (a) Clear → mission serviceable;

  (b) Inspection → major calendar-based or accumulated flight hour-based inspection;

  (c) xFHInsp → minor flight hour-based inspection;

  (d) Failure → failure-dependent repair;

  (e) Waiting → waiting for dock space; and

  (f) SpecInsp → non-recurring special inspection.

2. Maintenance Policy Assumptions

The term “maintenance policy” relates the inspection system to the weapon system. It encompasses all calendar- and flight-hour based inspection intervals and their relationships to each other. The impact of maintenance policy must be considered separately for retrospective and prospective usage:

- Retrospective – Because maintenance policy changed as of 1 April 2016, the policy implemented must reflect the historical data both prior to and after the critical date.

- Prospective – For projecting future system performance, the model uses one of four alternative maintenance policies, defined by user input, throughout the entire run.

3. Aircraft Assignment Assumptions

The aircraft assignment algorithm reflects subject-matter expert opinion. The implementation of the assignment algorithm ensures that flight safety rules apply. The monthly utilization budget is maintained under the assumption that demand completion is prioritized over fleet protection. If there is demand and at least one serviceable aircraft is available, this demand will be met even if the utilization budget of the currently assigned aircraft is fully consumed, regardless of whether this results in negative values for utilization budgets. The utilization budget is updated monthly and is assumed to be independent of the current utilization of the aircraft docks and residual inspection times.

4. Failure Generation Assumptions

Two alternative failure models are considered—one that pools all aircraft into a common structural form and one that treats each aircraft individually. The final implementation uses a separate Weibull distribution for each aircraft with parameters estimated from actual failure data. For aircraft where failure data is not available, we use the average of Weibull parameters estimated from the younger half of the fleet.

5. Failure Repair Duration Assumptions

Repair times are assumed to be independent and identically distributed for the entire fleet. This allows the use of bootstrapping for the prospective study. Once a failure occurs, it is repaired immediately with a randomly generated draw from the given repair time data set under the assumption that line maintenance capacity is unlimited, so queueing in line maintenance does not exist. This also applies to minor usage-based inspections and non-recurring special inspections. Effects due to personnel and spare parts availability are subsumed in the repair time data.

6. Maintenance Capacity Assumptions

Maintenance capacity is the number of available aircraft docks. It is determined by model input and assumed to remain constant throughout a single simulation run, regardless of the time period being covered.

7. Queueing in Scheduled Maintenance

Although the daily number of idle aircraft docks will be monitored in the model, this study does not focus on queueing protocols. The order in which aircraft are processed for phase inspections is ignored.

E. MEASURES OF EFFECTIVENESS

Law (2015) claims that "the measures of performance used to validate a model should include those that the decision maker will actually use for evaluating system designs" (Chapter 5, p. 247). In correspondence with actual fleet performance measures, the model generates four measures of effectiveness: (1) availability rate; (2) availability gap; (3) flight hour supply; and (4) mission completion rate. The model also produces daily dock utilization and queue length for output analysis.

1. Availability Rate

The most important measure of effectiveness in practice is the fleet availability rate, which is the daily number of aircraft available for flight operations divided by the total number of aircraft in the fleet.

2. Availability Gap

We include availability gap at the request of the sponsor. It is the difference between the number of available aircraft and daily demand. Goals include finding a parameter setting that results in maintaining a minimum threshold of serviceable aircraft, and quantifying the shortfall if the threshold is violated. These results are normally used in daily business at the regimental level, in communication with management, and in reports to the Ministry of Defense.

3. Flight Hour Supply

The daily flight hour supply of the fleet is the sum of flight hours until next major inspection across aircraft. This metric influences the yearly flight plan for the following fiscal year and reflects utilization of maintenance capacity. Fleet management aims to keep the flight hour supply constant. If flight hour supply is degraded, it always is a sign that either the fleet is being utilized too much or maintenance capacity is unable to keep up with the demand.

4. Mission Completion Rate

Mission completion rate quantifies the proportion of the flight hour demand that is carried out in actual flight operations. When no serviceable aircraft are available or the assigned aircraft has a failure during a mission, the residual demand is counted as missed demand.

F. DATA AND INPUT DATA MODELING

1. Fleet Data

Live fleet data was provided by the sponsor using SASPF, the official operation management system of the German armed forces. All logistical information on the aircraft fleet throughout daily flight operations is collected, maintained, and kept available online for distributed access and evaluation on all levels in operational processing by the German Army. Because the data is classified, equipment with secured access for modeling and analysis was provided by the sponsor to ensure proper data handling. Therefore, data usage in the scope of this work is presented to a limited degree to demonstrate the techniques pioneered in this study and to provide insight to the validation process of the final model design. The results presented in Chapter IV are anonymized and have been confirmed for public release by the sponsor.

A subject-matter-expert team in the system in-service management department for the TIGER fleet was commissioned to support this thesis. Regular phone conferences were held to discuss ongoing development, challenges, and interpretation of the data. This dialog opened new perspectives and possibilities of analysis to the entire study team.

Fleet data prior to January 2014 is not used for modeling purposes, because of transient behaviors produced by the small fleet size and a variety of extraordinary events such as unorderable spare parts due to missing material data, unclarified warranty issues with industry, and the learning curve of maintenance personnel. In addition, the Afghanistan mission from spring 2013 until summer 2014 is excluded, because that period reflects combat conditions. Therefore, our analysis is based on data, including daily flight hours for aircraft, for 2015 and 2016 only. A work agreement with the sponsor specified 1 April 2015 as the starting point of the simulation study.

Data used for this study includes

- daily flight hours per aircraft for 2015 and 2016;
- aircraft failure data with short problem description, open date, close date, aircraft accumulated flight hours (cell time) at time of appearance, and the corresponding failure repair times for the period 2014 to 2016;
- maintenance capacity for scheduled maintenance;
- inspection turnaround times for major and minor scheduled inspections;
- delivery (CoC) dates for new aircraft deliveries from industry;
- fleet state at start time of simulation ($\mathbf{t_0}$) with cell time, current state (clear, inspection, failure), residual time/flight hours to maintenance or residual turnaround time/failure repair time and age; and
- aircraft status history with description for period 2014 to 2016 including past inspection cycles, failures and non-recurring special events.

2. Input Data Modeling

The factor space examined in this study spans the following eight items: maintenance policy (option 1 to 4); simulation runtime (number of days); yearly flight plan (average number of yearly flight hours for each aircraft); maintenance capacity (number of aircraft docks); failure repair times; MTBF; and inspection turnaround times for major usage-based and calendar-based inspections. Other stochastic features are used, which are directly implemented into the model. All other parameterizations of the model are held invariant. In total, the model input spans seven input factors, five additional parameters with their distributions (if applicable), and fleet status information at $\mathbf{t_0}$. Important model inputs are described briefly in the following sections.

3. Fleet Status at $\mathbf{t_0}$

To determine fleet status at $\mathbf{t_0}$ (1 April 2015), the aircraft tail numbers with their corresponding cell times, which is the number of flight hours accumulated until that point in time, flight hours and time until next inspection, its operational state, and age were collated in a CSV-file. While cell times, operational status, and residual maintenance turnaround times were given metrics, all other variables had to be derived from the data. The following parameters define values for each aircraft upon initial entry into the study:

- Tail (ID) number
- Delivery Date: maximum of zero and the number of days from $\mathbf{t_0}$ to the delivery of the aircraft
- Age: difference between $\mathbf{t_0}$ and CoC date in number of days;
- Cell time: number of accumulated flight hours (total hours flown)
- Flight hours until next flight-hour based inspection: difference between cell time and the closest value, which has a common divisor of flight hours defined by the inspection system in flight hours;

- Calendar days until next calendar-based inspection: difference between date of last inspection according to inspection system;
- Residual repair and overhaul times: number of days left until measure concludes; and
- Parameters for failure generation: shape and scale parameters for Weibull distributions, as described in Section F.7 of this chapter.

4. Fleet Size

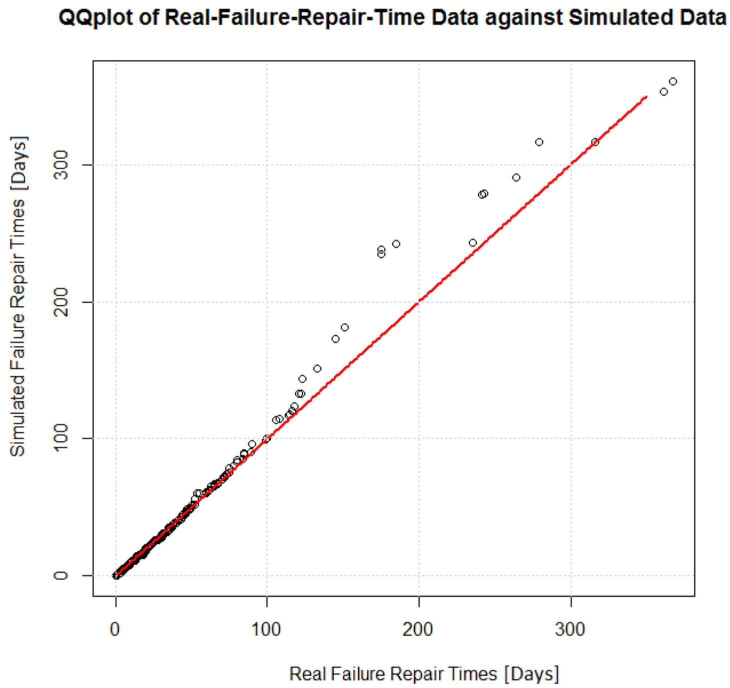
Fleet size is initially determined by the number of aircraft in the fleet at $\mathbf{t_0}$, which is the number of rows in the corresponding input CSV-file. The variable is updated each day in the simulation since aircraft join the fleet upon their delivery dates.

5. Yearly Flight Plan

The yearly flight plan defines target values for fleet utilization broken down to the individual aircraft. It contains the number of flight hours planned for each aircraft per year.

6. Maintenance Capacity and Inspection Turnaround Times

Turnaround times for major inspections and maintenance capacity are strictly determined by input factors given by the design matrix. However, turnaround times of minor inspections and non-recurring special inspections are determined through bootstrapping from the actual data, which is directly coded into a list. The bootstrap technique executes random draws from the list of turnaround times and assigns the variable that maps the corresponding property of the aircraft object that is due for maintenance with it. This approach provides two advantages to the analyst: (1) accurate validation results (see the Quantile-Quantile plot (QQ-plot) presented by Figure 7 and (2) easy adaptation of the model to another aircraft type. The downside of bootstrapping is that, in small samples, the tails of the distribution may be underrepresented.



QQ-plot shows a very accurate mapping of real data through simulation in the interval [0,120] days and deviation in upper segment [121,>300]. The deviation is due to sparsity of the data with respect to larger repair times.

Figure 7. QQ-plot of Bootstrapped Simulated Repair Times versus Real Data with Unprocessed Failure Repair Times of 2015 and 2016

Besides inspection thresholds—the number of accumulated flight hours or time at which an inspection becomes due (i.e., mandatory)—only lists of repair times used in bootstrapping need to be updated.

7. Aircraft Failure Generation

Occasionally an aircraft has a malfunction of some subsystem or component due to various reasons such as failure of an electronic component or fatigue crack of a mechanical structure. These events are defined as failures. Although failures always have to be repaired in the long run, there are different types of failure. Failures that do not need immediate attention are defined as minor failures, while failures that force an aircraft to be grounded for repair immediately upon detection are defined as severe failures. In practice, repair of minor failures is allowed to be postponed to the next inspection or to a period where the aircraft is undergoing some maintenance tasks (e.g., inspections, TCI replacements, or severe failure repairs). Therefore, the event is noted in the aircraft maintenance log file and the aircraft status, but in fact the aircraft is still serviceable for flight missions. The downside of this method is often a delay in inspection turnaround time, especially if the spare parts or the specialists needed are not available. For purpose of this work, these failures are defined as type 2 failures, which will not affect inspection duration because the equipment level is not implemented yet. All other failures are type 1 failures, which need immediate attention and cause downtime of the affected aircraft. All failures generated by the simulation model are in fact type 1 failures, therefore causing downtime and reducing fleet availability. To make sure used failure data covers type 1 failures properly, repair times are carefully broken down to the actual time needed for repair in practice. Time intervals indicating postponement, in which aircraft actually remain serviceable, are kept out of the data. Although two methodologies were tested during this study, only one will be used for deriving the final results.

a. Calendar-Based Failure Scheduling

In the first approach, data provided by the TIGER management department was used to count monthly failure packages over the interval January 2014 to December 2016. All failures at a certain cell time were viewed as a failure package entity. Therefore, at any given cell time, there could only be one failure package. After preparing the data, 95% confidence intervals were computed for accumulated failure packages per month for each aircraft. The corresponding confidence bounds, normalized to the simulation workday calendar, were then used as ranges for 53 of the 58 factors in the NOB spreadsheet for building the input design matrix used in the preliminary simulation experiments. In the simulation, these noise factor inputs are used to feed into an exponential distribution, which stochastically determines the time to next failure on the workday-based simulation calendar. Each time a failure is generated, the computed time until next failure is added to the current model time and used for scheduling the next failure event connected with the corresponding aircraft.

b. Usage-Based Failure Scheduling

According to Nelson (1982), Meeker and Escobar (1998), and Kalbfleisch and Prentice (2002), a common way to model reliability in the engineering community is to apply a proper parameterized Weibull distribution to generate mean times between failure (MTBF). In addition to MTBF derivation, the Weibull distribution is used for many applications in engineering like material strength modeling due to its variety of shapes. This makes it extremely flexible in fitting data and suitable for different modeling purposes. To fit suitable Weibull parameters to given aircraft failure data, a maximum likelihood estimation technique was used by utilizing the *survreg* function of the survival package in *R* (see Kalbfleisch and Prentice (2002), Chapter 2.2 for further information). The given aircraft failure data of 2014 to 2016 contained over 3,000 failures in total and roughly between 25 to 200 unique failures for each individual aircraft. The mean frequency of failure per aircraft is $\mu_{fail\text{-}AC}$ = 85 and its standard deviation $\sigma_{fail\text{-}AC}$ = 46. To achieve proper Weibull parameters for aircraft reliability, the following steps were executed:

1. All aircraft with fewer than 10 data points were removed from the data. For these aircraft, an averaged value of an age-dependent selected subset was used to derive the parameters.

2. Times between failure (TBF) were computed by taking the difference between the cell times of failure i+1 and failure i. To avoid censoring, the first and last observations were not used.

3. All failures with the same cell time, which are failures that happened or were revealed at the same time, resulting in a TBF of zero, have also been removed from the data.

4. For indexing purposes, a vector containing all the unique tail numbers was created.

5. While looping over the tail numbers, a parametric survival regression model is fitted to the data of each aircraft by using the survreg function in R.

6. In a final step, shape and scale parameters are derived from the regression model called sl1 by using equation 1 and 2 below.

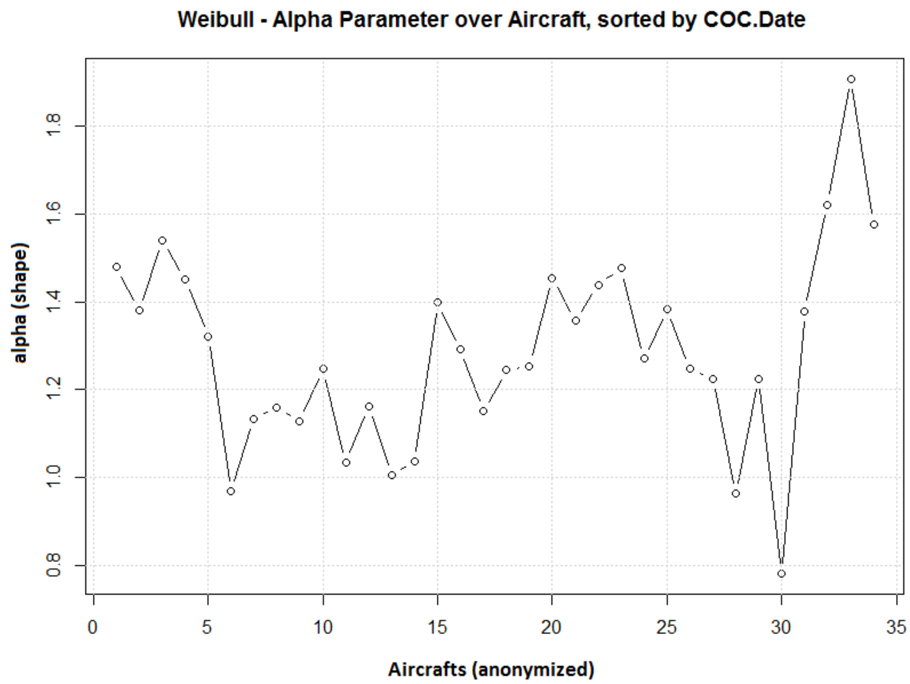
$$\alpha_{tail} = \frac{1}{sl1\$scale} \tag{1}$$

$$\beta_{tail} = e^{sl1\$coef[1]} \tag{2}$$

7. The generated Weibull parameters were then added to the CSV-file containing all t0 input data for automated input streaming.

Although both methodologies showed plausible results in model validation, the calendar-based model excludes the assumption that an increase in usage affects aircraft reliability. Usage-induced wear and tear effects, which in practice lead to degrading reliability, would be kept out of the scope of the model. As a result, changes in fleet utilization (yearly flight plan) would not affect aircraft reliability and hence would not affect fleet availability in the simulation results. Since the outcomes of a simulation model including this method for failure generation would not be able to reflect the impact of usage as an input factor on fleet availability, the calendar-based failure generation model is considered a non-suitable fit for systems behavior of the underlying real fleet. Therefore, the usage-based Weibull model for aircraft reliability has been chosen over the calendar-based exponential model to fill in that part.

Two possible layouts for the usage-based methodology including a Weibull distribution model were reasonable: use of a common shape parameter for the fleet and unique scale parameters for each individual aircraft, and unique parameters for each aircraft, because of their individual failure behavior. Figure 8 shows the actual results for shape parameters across the fleet gained from the maximum likelihood estimation procedure in direct comparison.



Due to classification of the data, these results have been anonymized with respect to tail numbers. $\mu_\alpha = 1.29$, $\sigma_\alpha = 0.22$

Figure 8. *α* - Parameters for Aircraft Failure Generation Weibull Model directly derived from Failure Data, sorted by Aircraft Delivery Datum

As is easily observable from Figure 8, shape (alpha) parameters derived from the data are significantly different from aircraft to aircraft. In particular, results for younger aircraft tend to differ from the mean with great variability. A possible reason could be the young age of the fleet or simply aircraft system complexity. Therefore, the decision was made in favor of individual alpha parameters in acceptance of an increase in input data volume.

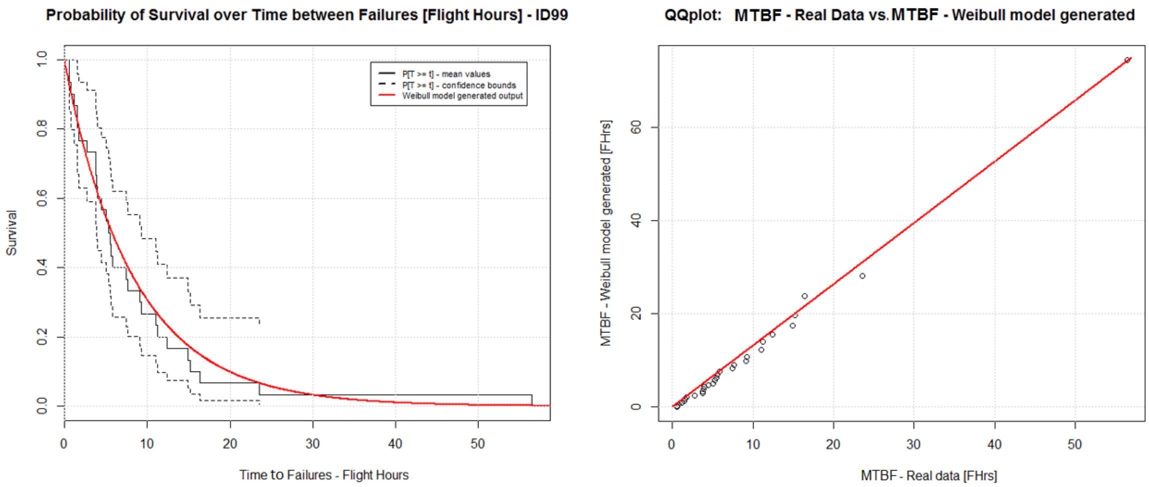
Table 1 contains the distribution of the difference between the Weibull model generated MTBF values across the fleet normalized with respect to the oldest aircraft in the fleet, to present the variability in value without revealing the true magnitude. On average, aircraft across the fleet have a 66% higher MTBF than the reference. The maximum deviation is 205%, while the standard deviation indicates a fluctuation of 52%. This enforces the necessity to implement individual aircraft objects instead of a homogenous fleet in order to achieve a suitable model fit for the TIGER fleet.

Table 1. Difference in MTBF Generated by the Weibull Distribution Fit Across the Fleet Normalized to the Mean MTBF of the Oldest Aircraft in the Fleet

1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
2.05	0.33	0.98	0.48	0.74	0.57	0.63	1.30	2.16	0.94	0.66	0.94
13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1.02	0.56	0.96	0.72	1.23	0.06	0.24	0.90	0.13	0.54	0.19	0.14
25	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**		
0.47	-0.05	0.85	0.97	0.28	0.30	-0.11	0.72	0.60	0.00		

Note: mean difference μ_{Fleet} = 0.66, standard deviation of difference σ_{Fleet} = 0.52.

Once the maximum likelihood estimation procedure of the Weibull parameter derivation for aircraft TBF distributions was done, results were tested for goodness of fit. A Kolmogorov-Smirnov-Test applied using the *ks.test* function in *R* by Marsaglia, Tsang, and Wang (2003) was performed on both the given data sample and the values generated by the corresponding Weibull model fit. Applying this method, a two-sample hypothesis test was performed, testing whether both samples come from the same continuous distribution. The resulting p-value of the hypothesis test is 0.8655, which indicates very strong empirical evidence in favor of the Null Hypothesis. Therefore, there is no basis to believe these two samples come from different continuous distributions. A visual representation of the Weibull model-fit for the same aircraft can be observed in Figure 9, where the plot shows the survival function (probability of survival) along with Weibull random numbers generated with the corresponding parameters achieved through maximum likelihood estimation (part (a)) and a QQ-plot, which covers a direct comparison of real TBF data quantiles with the Weibull generated quantiles (part(b)).



Plots shown are produced from data of an anonymized randomly chosen aircraft of the fleet in anonymized presentation and the Weibull values generated with the corresponding parameters.

Figure 9. (a) Survival Function (1-CDF) with 90% Confidence Interval based on generated Data Gained from Weibull Fit (left), (b) QQ-plot of Real Failure Data versus Weibull Generated Values (right)

To enforce validity of the estimated parameters and be efficient with it, one aircraft was picked randomly to show the methodology considered to exemplify that for the whole fleet. Since the generated data (red) models the mean of the real data (black) very closely, these results are assumed to represent a good model fit for aircraft reliability.

8. Failure Repair and Selected Inspection Turnaround Times

Failure repair times are modeled in the same way as the minor inspection and special inspection turnaround times. By using bootstrapping from embedded real data, the number of days for the downtime interval is drawn each time a failure occurs. The same data set will be used for bootstrapping failure repair times in all simulation runs performed. Although different failure repair time sets could be used to model failure repair time in more detail, or a slight modification of the code would allow the data set to be varied during an experiment, those possibilities are not included in this study.

9. Side Products

As side product from data analysis, the probability of survival with respect to time $P[T \geq t]$, which is the probability that an aircraft survives at least t hours before failure, can be evaluated and visualized by plotting the survival function. These results can be differentiated in terms of expected downtime for each aircraft by using the *survfit* function on the corresponding subset of the failure data in *R*. A second side product is determination and visualization of flight hour-based aging of aircraft by using a simple linear regression model on the given cell time data.

G. SIMULATION INPUT

1. General Overview

The simulation model requires a fair amount of input data. This input can be separated into two classes: (1) variable input that can be changed to study a subset of important input factors, different aircraft types, or a subset of the fleet and (2) unaltered input lists or parameter distributions that strongly depend on fleet data and do not change frequently over time like the set of historical failure repair and inspection turnaround times. They are implemented directly into the code and utilized by bootstrapping on the go. Furthermore, the fleet model is designed to take variable input by command-line arguments and an input stream based on CSV-files.

The simulation model can be run in two different ways. For presentation of time series plots, time series outcome data is needed for response variables of interest at certain fixed design points of the response surface. For example, to generate results for model validation purposes, the simulation model is initialized with the exact input parameters derived from given data of the desired time period. Then the simulation is replicated 1,000 times with those settings to get statistically meaningful results. The input CSV-file only contains one single input row in that case. In contrast, for exploring factor variations, the input design CSV-file can contain many rows, one for each design point. A smaller number of replications can be conducted if the computation time is a concern.

2. Command-Line Input

Command-line input includes all input factors that are evaluated in this study as well as the name of a file that contains the fleet status information at $\mathbf{t_0}$. Input factor values are determined by the NOB input design matrix and fleet data input, both stored in CSV-files. Input for each simulation run corresponds to one row in the design CSV-file, which is used by the "rundesign_general" *Ruby* script. This file also contains the file name for the fleet status information and the simulation runtime. The CSV-file containing fleet status information at $\mathbf{t_0}$ includes all aircraft-dependent input data like delivery date, age, operational status, residual repair and turnaround times, the Weibull parameters and a few more. These files can easily be modified to study the fleet from a different starting point, a subset of the fleet, different fleet sizes, or even a fleet with a different aircraft type, vehicle fleet or machinery inventory.

3. Embedded Model Parameters

The model has several parameters that are currently hard-coded, such as turnaround times of minor inspections, special inspections, and failure repair times. While using bootstrapping on the basis of given assumptions explained earlier, these data sets are directly taken from the given fleet data and coded into the model as lists from which to pull values. Although slight modifications of the code would allow different data sets to be selected and tested via the use of an artificial input factor, they are assumed to remain unchanged for the desired time frame for this study. These data sets stored in lists will have to be updated, if one wants the model to be adaptable to changes of fleet characteristics over time and still keep credibility of results.

4. Simulation Analysis Approach

Our goal is to sample the simulation model in a way that facilitates metamodeling. A metamodel is a statistical model that characterizes the simulation model's input-output mappings, and can be used both descriptively and inferentially. The sampling strategy is based on a designed experiment. Details of the simulation modeling considerations are discussed in Chapter III, and details of the simulation analysis appear in Chapter IV.

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III. IMPLEMENTATION OF SIMULATION MODEL

A. SIMULATION ARCHITECTURE

Chapter II introduced basic ideas and functionalities on which the implemented simulation model is based. In this chapter, the focus is on the actual implementation. The first subsection gives a brief introduction to *SimpleKit*, the modeling toolkit used to build the simulation. The second subsection discusses the time advance mechanism. Subsections three through six cover the input data interface, the data structures used for implementation, the design of the model using an event graph, and an overview of the model logic. Each event is structured as a unique method. Subsequent sections describe each method's logic. Finally, this chapter concludes with the output design.

1. SimpleKit

As discussed in Chapter II, a DES model seems appropriate for this study. *SimpleKit* by Oliver and Sanchez (2015) is an object-oriented discrete-event modeling toolkit based on event graphs introduced by Schruben (1983) and then extended by Sargent (1988) and Som and Sargent (1989). *Simplekit* is implemented in the *Python* programming language. It provides event scheduling and management but leaves random variate generation to *Python*'s standard libraries. User-defined models are implemented as subclasses of the *SimpleKit* class.

a. Functionality

SimpleKit manages the ordering and execution of events. An event is defined as a point in time at which the system state changes in some fashion. Events have no duration, and are implemented in a *SimpleKit* model as methods that perform state transitions or conditionally schedule further events. The modeler is required to supply an 'init' event which initializes the system state and schedules one or more model-specific events in order to initiate a run. The model terminates when no further events are scheduled, or when an explicitly defined end-state is recognized and the “halt” method is invoked.

b. Aircraft Fleet (Subclass of SimpleKit)

The fleet model object is a subclass of class *SimpleKit*. It inherits all the properties and methods of that parent class. Thus, all scheduling tools are built-in. Model-specific data—in this case fleet data—is initialized for the model via its constructor. Design architecture, implementation, initialization, and event flow of the aircraft fleet model are described in detail in Chapter III.

2. Time Advance Mechanism

The model was implemented using a time-step formulation with daily intervals. Each workday is executed without exception and evaluated separately, even if nothing happens. Jumps along the time line due to events are not allowed. Flight operations, inspections, failures, and special events are tallied daily. For each scheduled workday, a standard workflow is implemented which determines whether events influencing fleet dynamics do or do not occur. Since aircraft operations and maintenance workflow in practice, especially in peacetime, are strongly driven by common work schedules on a daily basis, this methodology is assumed to be suitable for this problem. In practice, measures of effectiveness like availability rate are also monitored on a daily basis, which demands a similar evaluation through the model to ensure a suitable fit of the actual model response for the underlying system.

To keep the time roster consistent, time intervals for maintenance tasking in general are normalized to complete workdays. Once a failure happens or an aircraft is due for maintenance, its status will be updated immediately to ensure flight safety, but execution of workflow starts no earlier than the next workday. This approach deviates from practice, but simplifies the model while still providing enough fidelity to suit our needs. This model is formulated as a terminating simulation—the run-length is a deterministic criterion provided as a model input that defines the point in time at which *SimpleKit* halts the simulation.

3. Input Data

Input data is acquired by two mechanisms. First, information about the fleet status at $\mathbf{t_0}$ is stored in a CSV-file. Second, command-line arguments are provided with the invocation of the *Python* script—the file name of the input CSV-file, followed by values for the following six factors: (1) maintenance policy, (2) simulation runtime, (3) planned yearly flight hours per aircraft (fleet utilization), (4) maintenance capacity, and the inspection turnaround times for (5) flight-hour-based and (6) calendar-based inspections. Once properly called, the program reads and parses the CSV input file line by line. This CSV-file contains all the aircraft, one per line of input, including aircraft with delivery dates after the initiation date $\mathbf{t_0}$. Using this approach, the number of aircraft is not limited due to the generic model design used, but is determined by the size of the CSV-file. The position of each piece of information is standardized. The model checks the delivery date of each aircraft on initialization, schedules the deliveries for aircraft with a positive (future) delivery date value, and starts the simulation with the subset of aircraft for which the delivery date is equal to zero. After all input information is processed, the fleet model is then started with all necessary input parameters.

4. Data Structures

Other than the aircraft object template design for the individual aircraft, all variables are organized with basic *Python* data-types. This section focuses on the details of three basic objects used for fleet management: (1) the Aircraft object itself, (2) the Aircraft Fleet, and (3) the Aircraft Assignment list. A side note regarding distributions implemented using the bootstrap method concludes this section.

(1) Aircraft Object

Each aircraft is created as an instance of class “aircraft,” a customized *Python* object. The constructor initializes each aircraft using all the properties read from the CSV-file along with some auxiliary variables used for flight assignment prioritization and failure generation (Figure 10).

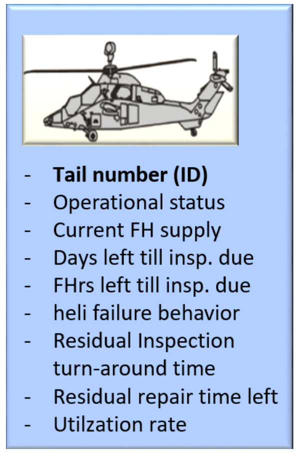


Figure 10. TIGER Aircraft Object

Later, it can easily be expanded with equipment objects for key equipment like engines or main gear boxes along with their properties and maintenance policies. The aircraft class is not TIGER specific—it can be used for other aircraft types.

(2) Fleet Object

The fleet is a globally available collection of aircraft objects organized in a *Python* dictionary. A dictionary stores and retrieves objects by associating them with a “key” value. In the fleet model, the aircraft IDs or tail numbers associated with aircraft objects are used as the unique keys to access aircraft for flight assignment or any kind of maintenance event processing. Aircraft entities can be removed or added any time.

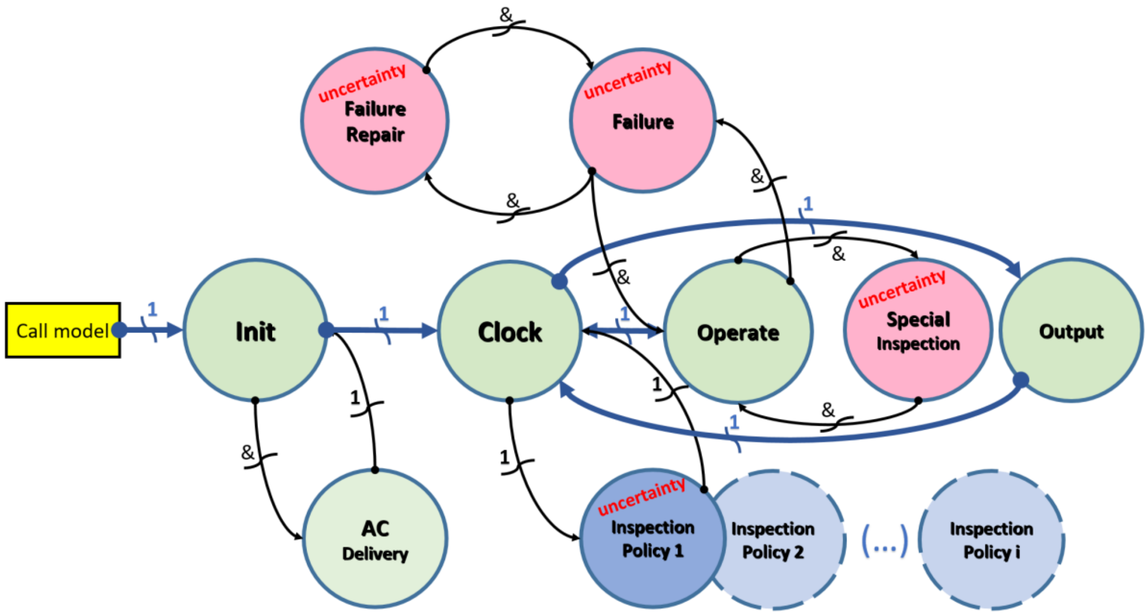
(3) Assignment List

The assignment list is a global *Python* list object. Each day, the fleet is checked for serviceable aircraft. Before generating decisions for flight assignment, a copy of serviceable aircraft will be stored in the assignment list. A list object is sortable by any kind of variable, which is very useful for aircraft flight assignment. Also, aircraft objects can be removed from either the lower or the upper end of the list at any time. Once the *operate* method is called, aircraft IDs are chosen from the assignment list, but any updates to the associated aircraft data are stored in the fleet dictionary.

Lists are used throughout the program for other purposes. Most input and output variables, such as the real failure repair times, are stored in lists. The bootstrap method uses a list of historical repair times from which it randomly samples each time a failure is generated.

5. Event Graph

This methodology for describing event flow was first introduced by Schruben (1983) and then extended by Sargent (1988) and Som and Sargent (1989). According to Buss (1996), event graphs are “a way of graphically representing discrete-event simulation models” (p. 153, abstract). Furthermore, he states that “the Event Graph is the only graphical paradigm that directly describes the event flow of a discrete-event simulation model. Event graphs have a minimalist design, with a single type of node and two types of edges with up to three options. Despite this simplicity, Event Graphs are extremely powerful” (p. 153, abstract). Each event is represented by a unique node. Directed edges, a.k.a. arcs, depict scheduling relationships between events. Edges are annotated with a delay (which can be zero, but never negative), and scheduling can be state-dependent. The basic events and scheduling connections of this aircraft fleet simulation model are presented in Figure 11.



This discrete-event graph shows states and state flow of the TIGER fleet model. Aircraft delivery and basic functionalities are highlighted in green, scheduled maintenance in blue, and unscheduled events demanding maintenance actions in red. Arcs always executed without condition are marked with the character "1" and arcs executed based on conditions with "&."

Figure 11. Event Graph for the Implemented Usage-based Discrete Event Simulation Model

6. Model Logic

Each event node shown in Figure 11 is implemented as a unique *Python* method. The event logic for each is described in detail in the next section.

The model is invoked by calling *SimpleKit*'s *run* method for the fleet model instance. *Run* kick-starts the model by invoking the mandatory *init* method. It initiates the fleet by instantiating all aircraft objects from the corresponding input data and scheduling aircraft deliveries according to the specified CoC-date values. Aircraft with delivery dates of zero are available immediately. The *init* method then schedules the first workday without any delay. From this point, event logic schedules a subset of events in recurring but not necessarily identical order. Subsequent event scheduling is handled by *SimpleKit*'s pending event list, which is populated by *schedule* operations corresponding to the edges of the event graph.

After closure of a preceding workday, which always happens after derivation and storage of the current fleet status in the status board, a new workday is scheduled until the defined halt criteria are met and the simulation run terminates. Each day, aircraft demand will be satisfied by flight operation assignments until there are no more serviceable aircraft left in the fleet due to failures, special inspection events, or scheduled maintenance. While failure events and special inspection events occur stochastically according to Weibull and Bernoulli models, respectively, scheduled maintenance is performed according to the deterministic requirements of the inspection system under evaluation. Policy changes are allowed over time during a single simulation run, but on any unique workday there can only be one maintenance policy active at a time. Hence, its selection is optional in the event graph. This selection is either done by input parameter or by a “hard-coded” model time value utilizing the *option-switch* variable. Also, each aircraft entity can only have one unique status at any given time. It is either serviceable (clear), in scheduled maintenance (major or minor usage-based or calendar-inspection), special-inspection (specInsp), in failure state (failure), or waiting for maintenance (waiting). Due to usage-based failure generation and the type-1-failure-only assumption described in Chapter II, the failure state can only be reached from the *operate* event before or during a flight operation. After a failure occurs and the obligatory failure repair procedure has been scheduled, *Python* resumes execution of the *operate* event where it left off, and further flight assignments will be conducted until there is either no demand or no aircraft left to meet the demand. After completion of *operate*, the program flow deterministically returns to the *clock* event, which then proceeds with execution of the maintenance policy and status board output generation. This task flow is repeated for each workday until the program terminates.

B. MODEL INITIALIZATION

1. *Init* Event

The *init* method handles all input data provided by the model *run* invocation. It instantiates and initializes variables such as aircraft objects, the fleet dictionary, and failure repair times, as well as auxiliary variables for output design and testing purposes. All variables needed by the simulation are defined as instance variables of the fleet model class, which makes them accessible throughout the scope of the model and the duration of the run. If future model revisions are necessary, the user should use the *init* method to change simulation parameters or fleet condition, or to insert new or updated data as the aircraft fleet is evolving over time. Finally, the first workday gets invoked by scheduling the first *clock* event.

2. Instantiating Aircraft Entities and Fleet Object

While processing each aircraft given by the fleet input CSV-file, an *aircraft delivery* event gets scheduled if applicable, and failure and scheduled maintenance data are used to set the aircraft's current state and update available maintenance capacity, which includes scheduling of a *failureRepair* event in case an aircraft failure occurs at or occurred prior to $\mathbf{t_0}$. The delay is determined with respect to the residual repair time given by input data from the CSV file.

After finalizing the instantiation process, each aircraft will be stored in the global fleet-dictionary with its tail number or ID used as a unique key for accessing the objects. The properties of *Python* dictionaries provide nearly instantaneous access to the aircraft data. Also, fleet size is not limited with respect to specific data type constraints. It is only bounded by given memory size of the computer system on which the model is executed. The code structure for aircraft and fleet instantiation is triggered by the length of the delivery date list handed over with the data at time of model startup. Since every aircraft has a delivery date, which is either zero or greater than zero, the fleet instantiation is not bounded by a specific fleet size. This generic design adapts automatically to any given fleet size, determined by the number of properly filled lines in the fleet data input CSV-file.

3. Aircraft Delivery

All aircraft delivery events are scheduled during fleet initializing by the *init* method prior to the first workday. Although aircraft objects subject to delivery are already initialized and part of the fleet, their main status remains not serviceable (*False*) until the scheduled individual delivery event is executed. Also, failure scheduling is omitted and the maintenance calendar remains in freeze mode until the actual delivery date arrives. On the delivery workday, the main status of the affected aircraft is set to serviceable (*True*), all other properties are updated, and the first failure is scheduled. Finally, fleet size is updated.

C. TIME MANAGEMENT

1. *Clock* Event

The *Clock* method determines the daily event processing. The order of daily event processing is the same for each day (Figure 12). After aircraft and flight hour demand are generated, the fleet is scanned for serviceable aircraft. Each serviceable aircraft is added to the list used for flight assignments.

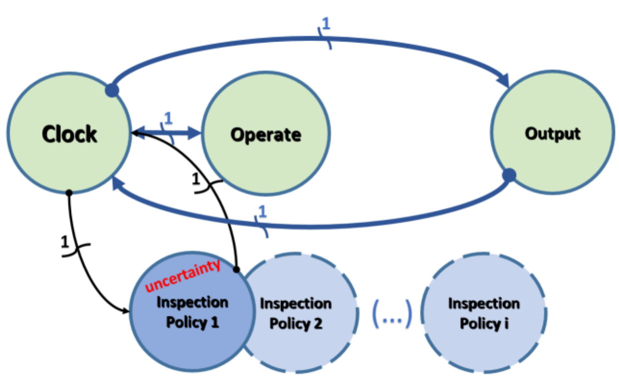


Figure 12. Partial Event Graph Showing Daily Event Flow of Major Events

While looking for serviceable aircraft, fleet data gets updated once each workday. Fleet data updates include: (1) increase age for all aircraft, (2) decrease workdays until next inspection, but only for aircraft not currently undergoing major scheduled maintenance, and (3) decrease residual inspection turnaround time for aircraft currently in inspection. These rules mean that aircraft are always aging, but the scheduled maintenance calendar is frozen for aircraft currently in major overhaul.

After iterating through the fleet, the assignment list gets sorted with respect to the utilization budget of aircraft to prepare the fleet for the subsequent assignment process. Finally, the major event methods highlighted in green in the partial event graph shown in Figure 12, as well as the maintenance policy highlighted in blue, are invoked once each day in the following order: *Operate*, *ProceedSchedMaint*, and *StatusBoardOut*. The maintenance policy to be used is determined by the policy *optionSwitch* variable, determined either by an input parameter or "hard coding." *StatusBoardOut* concludes by scheduling a *clock* event for the next workday, and the process starts again.

2. Daily Demand Generation

Generation of daily aircraft demand follows some simple mathematical rules. The yearly flight program for the fleet ($\boldsymbol{YFP_i}$) is defined each year prior to year $\boldsymbol{i}$ as the sum of the average monthly flight programs, defined as utilization rate $\mathbf{u_i}$ for each aircraft, multiplied by the number of aircraft in the fleet $\mathbf{n_{AC}}$ and the corresponding monthly seasonal weight $\boldsymbol{w_j}$ for each month $\boldsymbol{j}$. This seasonal factor describes the proportion of the yearly flight program to be flown in month $\boldsymbol{j}$**,** and provides an opportunity for the user to add a seasonal effect to the model such as change in demand of flight hours throughout the seasons in a specific year $\boldsymbol{i}$. The yearly and monthly flight programs are given by Equations 3 and 4:

$$YFP_i = \sum_{j=1}^{12} (n_{AC} * u_i) * w_j = \sum_{j=1}^{12} MFP_{ij} \quad \text{, for each year } \boldsymbol{i} \qquad (3)$$

$$MFP_{ij} = n_{AC} * u_i * w_j \tag{4}$$

for $\boldsymbol{i}$ ε [1,6), $\boldsymbol{j}$ ε [1,12] and $\mathbf{w_j}$ ε [0,1].

Because there is no significant evidence of seasonal effects in the fleet data, the monthly weights $\boldsymbol{w_j}$ are held constant in current model runs. The average number of monthly missions is derived by dividing $\boldsymbol{MFP_{ij}}$ by the mean flight hours per mission $\boldsymbol{\mu_{FH/Miss}}$ derived from given fleet utilization data. Normalized by 22 workdays each month results in the average number of missions per workday. This represents the mean daily aircraft demand and is given by Equation 5:

$$\mu_{AC} = \frac{MFP_{ij}}{\mu_{FH/Miss} * 22} \tag{5}$$

Since daily demand is assumed to be stochastic, a truncated normal distribution is utilized with $\boldsymbol{\mu_{AC}}$ and $\boldsymbol{\sigma_{AC}}$ = 0.5 to model non-negative demand generation. The final derivation of daily aircraft demand is presented in equation 6:

$$D_{AC} = \mathrm{round}(\max(numpy.random.normal(\mu_{AC}, 0.5), 0)) \tag{6}$$

Derivation of daily flight hour demand is much simpler. By using $\boldsymbol{\mu_{FH/Miss}}$ and $\boldsymbol{\sigma_{FH}}$,

$$D_{FH} = \max(numpy.random.normal\left(\mu_{\frac{FH}{Miss}}, \sigma_{FH}\right), 0) \tag{7}$$

During the validation process, using this methodology produced flight hours that are statistically indistinguishable from those actually flown in practice throughout the years 2015 and 2016. Hence, the approach was deemed acceptable.

3. Basic Modeling Features

Since the *Clock* event is responsible for scheduling daily basic tasks, it is the first event to be executed each day. The user can use it to schedule adjustments to the model at particular points in time, like prior to the beginning of a new calendar year. Since fleet behavior is subject to change over time, this may yield a more accurate fit of the simulation relative to the underlying fleet system, or simply offer capabilities for sensitivity analysis in a what-if scenario.

Driving factors for fleet behavior might change as the fleet matures. Failure repair time distribution, for example, might change due to learning curve effects impacting maintenance personnel effectiveness. The user can change parameter distributions any time by updating the corresponding list yielding the desired distribution in the *init* method. It is also possible to define an upper bound for yearly flight hour demand or select different sets or subsets for bootstrapping from given fleet data like failure repair times.

D. AIRCRAFT ASSIGNMENT

1. Daily Flight Operations (Operate Event)

As described above, demand for aircraft and flight hours is generated by the *Clock* method each day. After the daily update of the aircraft objects is done, the assignment list is filled with serviceable aircraft, and aircraft are sorted by their utilization budget, the *Operate* method gets scheduled with zero delay and the aircraft assignment algorithm is executed as long as there is residual demand of aircraft and serviceable aircraft left to be assigned to flight missions. Although the assignment list should only be filled with serviceable aircraft by now, a lot of things can happen during daily flight operations. Aircraft could be subject to failure or become unavailable due to any kind of scheduled maintenance, because they are running out of flight hours, or because a special event occurs. To avoid basic rule violations, the assignment algorithm is designed to maintain the central rule hierarchy, including flight safety guidelines. It assures that aircraft subject to any kind of flight safety issue are removed from the assignment list and properly handled based on their situation, such that they cannot be assigned again until the flight safety issue has been resolved. The basic logic of the assignment algorithm is presented in Figure 13.

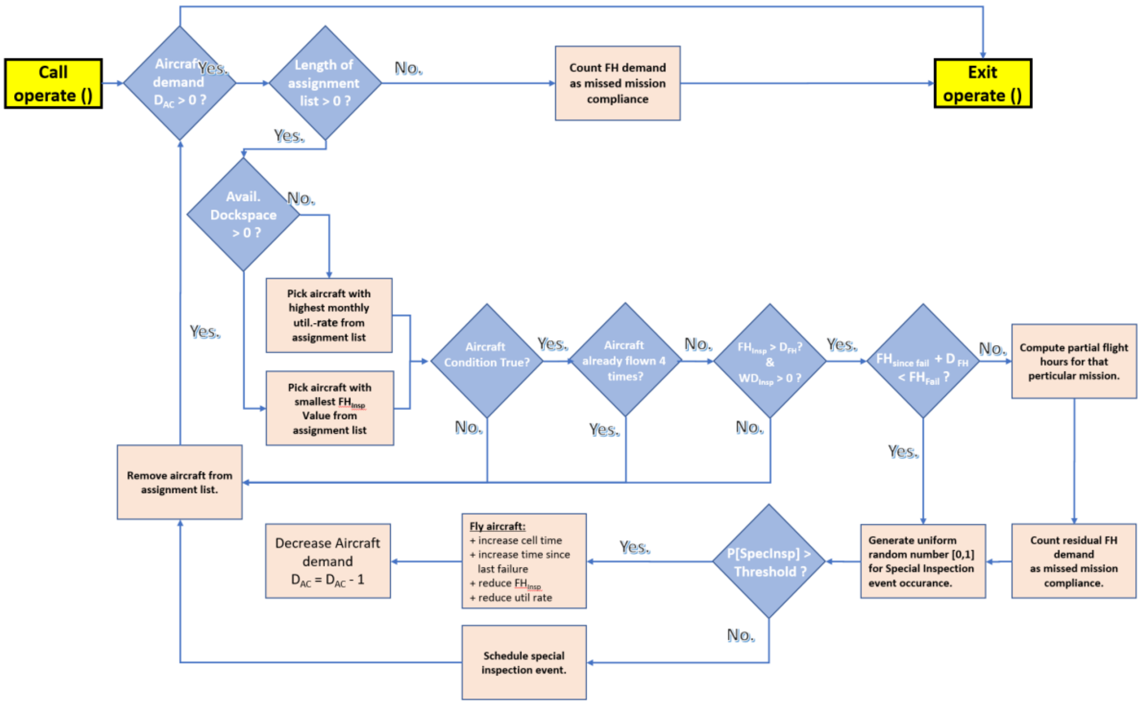


Figure 13. Aircraft Assignment Algorithm, Implemented in the Operate Method

Besides monitoring implemented flight safety regulations, the assignment algorithm has six major tasks:

1. Keep track of mission non-completion, which is the accumulated number of flight hours not flown due to aircraft failure and non-availability of aircraft.

2. Assure an equal load across the fleet by selecting the aircraft with the highest residual monthly utilization budget for flight missions unless dock space becomes available. Among other properties, the utilization budget is decreased and the assignment list is sorted with respect to utilization budget after each flight. Therefore, flight-by-flight other choices for aircraft assignment are forced, which assures the utilization load is dispersed equally across the fleet.

3. Improve utilization of maintenance docks by basing the selection on fewest flight hours until next inspection. This assures that the aircraft closest to its next scheduled maintenance becomes due earlier, to decrease dock idle times. In practice, this monitoring process is done by daily meetings. Updates are made based on estimation and experience. There are ways to implement this

process more realistically in the model, but that is an area for future work.

4. Schedule failure and non-recurring special inspection events as appropriate and remove affected aircraft from assignment list.

5. Ensure that individual aircraft cannot be flown more than four times per day. This feature provides assurance that no infeasible state occurs in cases of very high demand.

6. Perform assignment list management and update aircraft properties after each flight as needed.

Failure and special inspection events are conditionally scheduled in connection with each flight assignment based on random breakdown events or scheduled inspection times, the corresponding *Failure* and *SpecialEvent* methods are invoked directly. Once the sum of accumulated flight hours since last failure and the current demand exceeds the current *MTBFnext* value, the condition for a failure event is satisfied. The corresponding aircraft is removed from the assignment list and the *Failure* event method is executed. If this failure condition is not satisfied, a uniformly distributed random number between zero and one is generated prior to each flight, which is used to verify whether the special inspection threshold is undercut or exceeded. In case the threshold is undercut, a special inspection event occurs and the aircraft is removed from the assignment list. After completion of the method belonging to its corresponding event, *Python* resumes operations at the point of the method call. When there is no residual demand left or there are no more serviceable aircraft left in the assignment list, the *Clock* method resumes operation in the *Operate* method and invokes the *ProceedSchedMaint* method corresponding to the current maintenance policy.

E. FAILURE HANDLING

1. Update Aircraft Properties

Once the failure condition is satisfied, the impacted aircraft is removed from the assignment list and the *Failure* method is invoked directly with the corresponding aircraft ID. The *Failure* method only does two things: (1) updating the status and the corresponding properties of the aircraft object in the fleet dictionary and (2) scheduling its failure repair event. Since there are no constraints on line maintenance capacity, failure repair always starts immediately on the next workday using a bootstrapped failure repair duration. Hence, the residual repair time for a specific failure is reduced by one day every day until it reaches zero. It should be noted once more that although an aircraft cannot accumulate flight hours while in a failure state, the maintenance scheduling calendar is still active. While in repair, the time until next inspection is decremented every day.

2. Determine Failure Repair Time

Determination of failure repair times, which represent the delay for the failure repair event to happen, is done by bootstrapping from the list of real failure repair-time data. The resulting value is stored for testing purposes and used to schedule the failure repair event. This approach ensures plausible failure repair times, and can easily be replaced by a parametric distribution if one is deemed suitable.

3. FailureRepair Event

The *FailureRepair* method has a fairly simple task. This method updates the aircraft properties after repair actions are concluded. The overall status of the corresponding aircraft is reset to *clear* and its failure status is set to *False* with zero residual repair time left. Finally, its flight hours since last failure value is also set to zero and the next MTBF value for the next failure event is computed using the methodology described earlier.

F. INSPECTION HANDLING

1. Overview

The final task on each scheduled workday is the *ProceedSchedMaint* method, which applies the current maintenance policy. There are four variants of this method, which cover the four maintenance policy options evaluated in this study. These methods browse the fleet for scheduled maintenance conditions and manage scheduled maintenance for both general and special inspections. This includes initialization and closure of maintenance events, and a reset of aircraft status and management variables.

2. Minor Scheduled Maintenance Events

Minor scheduled maintenance events are usage-based inspections, which require a relatively small amount of work at the end of each interval. They are performed by the line maintenance company and are not currently subject to constraints in the model. To keep track of due dates, a designated variable yields the flight hours until next inspection, which is updated after each flight. *ProceedSchedMaint* initializes a minor scheduled maintenance event by updating the designated aircraft properties directly instead of scheduling it via *SimpleKit* methods. Residual turnaround time is updated by *Clock* each day. Once residual inspection turnaround time reaches zero, *ProceedSchedMaint* resets the aircraft status and flight hours until next minor inspection. During a minor usage-based inspection the major inspection calendar remains active. Therefore, turnaround times—which are also evaluated by bootstrapping from the given real data—affect residual workdays until the next major inspection.

3. Major Scheduled Maintenance Events

For TIGER major scheduled maintenance, there exist two basic types of major scheduled maintenance events: a flight hour-based and a calendar-based inspection. These inspections are considered major because they require a large amount of work with a high degree of aircraft disassembly. These inspections require an aircraft dock, specialized personnel, and a large amount of time. The aircraft management procedure implemented in the model is the same as for minor maintenance events. Each aircraft object possesses variables that track the inspection status and the residual turnaround time, which are updated each day. The only difference is that maintenance capacity is constrained. An aircraft only enters inspection if there is dock space available. If capacity is available and current demand for flight hours is larger than flight hours until next inspection, a usage-based major inspection is initiated for the affected aircraft. If workdays until next inspection reach zero before the flight hour criterion is violated, a calendar-based major inspection is initiated. If there is no dock space available, the aircraft due for maintenance is marked as *waiting* for maintenance through an update performed by *ProceedSchedMaint.*

Every major usage-based inspection also includes all required maintenance tasks of a major calendar-based inspection, but major calendar-based inspections do not include maintenance tasks of the major usage-based inspections. Hence, the set of maintenance tasks performed includes all required actions for justification of resetting the workday until next inspection condition. During a major inspection, the inspection calendar clock is frozen, and gets renewed after each major inspection.

4. Non-recurring Special Inspection Events

Although non-recurring special inspection events belong to the line maintenance domain and therefore are handled the same way and under the same conditions as minor scheduled maintenance events, they are scheduled via *SimpleKit**.*** Update of aircraft properties is done by an event method called *SpecialInspection*. Statements regarding inspection calendar and turnaround time generation likewise apply. Therefore, the inspection calendar is still active during the conduct of non-recurring special events, and turnaround times are determined with bootstrapping. Occurrences of non-recurring special inspection events are determined by a Bernoulli trial prior to each flight mission using a fixed probability estimated from the historical fleet data.

G. QUEUE MANAGEMENT

In practice, aircraft are monitored very closely by the fleet management departments of the corresponding units. Utilization budgets are updated continuously and aircraft utilization is updated instantaneously if necessary. Also, the limited fleet size has not imposed challenges to fleet management with respect to maintenance capacity so far. Therefore, queue management basically is done in practice by proactive fleet management to avoid of queueing. The underlying queueing technique applied in practice is “first-in-first-out” (FIFO). Given the projected fleet growth, this will not be possible in the not-too-distant future. Long inspection turnaround times and heavy utilization of the fleet will almost certainly lead to overload of maintenance capacity and long waiting times for maintenance facilities. Therefore, evaluation of queueing effects due to growing fleet size and analysis of maintenance capacity is a subject of interest for this study.

H. OUTPUT SPECIFICATION AND MODEL EXECUTION

1. Overview

For presentation and analysis of simulation output, two methodologies were applied: (1) Time Series and Likert visualization and (2) Multidimensional linear regression analysis covering the NOB metamodel results. Time Series plots generated for availability rate, inspection queue, and flight hour supply are produced with *R*. Likert plots are used to display deviation from a given daily aircraft availability threshold as requested by the sponsor. To generate these plots, complete time series sets of daily output data for each factor are required.

In contrast, for metamodel analysis, only summary statistics like the upper and lower decile and median (50^{th} quantile) for the whole simulated period are required for each response variable, collated with the mirrored input factor settings. For any single simulation run, one line of output is generated and written to an output CSV file. For validation of a single-scenario simulation analysis, 1,000 runs at the same input parameter combination are executed, while for each NOB simulation analysis six rotations of 512 design points (parameter combinations), replicated 30 times, result in 92,160 lines of output written in a CSV-file. The automated execution and output handling is done with the *rundesign_general Ruby* script provided by the NPS SEED Center, with input defined by the implemented fleet data and input design CSV files. The input factor values are matched to the outputs for each run, as required to fit metamodels that summarize the relationships between the input factors and the outputs of interest. To meet the needs of the user, the output can be generated either by using the NOB input design or single point analysis for time series data and visualization.

2. Output Generation (StatusBoardOut Method)

Model output is produced by the *statusBoardOut* method, which is called by *operate* as the last event each day. The status board method browses the fleet for aircraft status and flight hours until next usage-based major inspection at the end of the day. With this information, the status board method computes the current fleet availability ratio, as well as the ratios for each implemented aircraft status class. As a second step, the resulting values are stored in two corresponding lists which can then be sorted for quantile estimation. Because *Python* list objects are reference variables, sorting a simple copy would alter the original time series data so a deep copy is required for quantile estimation. At the end of each simulation run, the quantiles, number of special inspection events, and non-accomplished flight hours are evaluated. The number of non-recurring special events is derived by browsing through the list containing all generated Bernoulli trial probabilities for values below the given threshold. Quantiles for each response variable are determined by the tenth, fiftieth, and ninetieth percentiles of the corresponding sorted list of daily outcome values. In general, the output can be customized to meet the needs of the user. The design point settings for the factors and all output variables are combined in one large print statement, and the result is written into an output CSV-file by the *rundesign_general Ruby* script. *Python* prints lists as bracketed comma separated values. After suitable editing to remove the brackets, they can be read into virtually any analysis tool, such as *R*.

3. CSV Content

The output CSV-files generated contain the following elements.

(a) For single point simulation analysis:

- maintenance policy option;
- simulation runtime;
- yearly flight hours per aircraft;
- maintenance capacity;
- major inspection turnaround times;
- total number of aircraft failures, flight missions, special events, and yearly flight hour demand; and
- time series output for availability rate, deviation from aircraft threshold, flight hour supply, and rates for each aircraft status class.

(b) For NOB Output:

- Input factor settings of design points as in (a);
- lower decile, median, and upper decile for availability rate, deviation from aircraft threshold, flight hour supply, aircraft waiting for maintenance, and number of idling docks;
- total number of aircraft failures, flight missions, special events, and yearly flight hour demand; and
- missed flight hour demand due to aircraft failure and non-availability of serviceable aircraft.

I. EXPERIMENTAL SETUP

The experimental setup required for the model validation time series analysis requested by the sponsor is different than that for the NOB metamodel analysis. To show that the time step simulation model developed for the underlying aircraft fleet produces plausible results, a specific parameter setup corresponding to the given fleet data is used.

1. Validation Setup

The validation setup is a special variant of the general time series setup. It spans only the time frame from the 1 April 2015 to 31 December 2016. The validation simulation runs need to incorporate a switch in maintenance policy that occurred on 1 April 2016, making a transition in the special inspection threshold level and failure repair times in order to correspond with changes in the real data. Bootstrapping is done from two different data sets for 2015 and 2016. All input factors are set to values derived from the historical fleet data. This setup is treated as a single design point analysis, and replicated 1,000 times.

2. Time Series Setup

The time series setup is similar to that for validation, except that all standard input variables and factors are held constant throughout each simulation experiment. Standard input variables are changed case by case. The assumption is made that the parameter values used are valid for the entire simulated time period, which includes 2015 and 2016 but projects the fleet status four years into the future. This assumption influences the course of the entire time series. For example, one can choose a common value for yearly fleet utilization level while changing the inspection turnaround times as needed from experiment to experiment spanning the same simulation time frame. As a result, all results can be presented in one plot. In addition, the failure repair duration data set of 2016 yielding the already-improved repair times, as well as the implemented minor usage-based and special inspection turnaround times, are used for all time-series experiments directly implemented from given fleet data. All these internal parameters plus the non-recurring special inspection threshold remain unchanged throughout the simulation replications of each experiment. Another option for analysis provided is the change of aircraft reliability parameters. This is done by feeding the simulation model through a modified fleet input CSV-file.

3. NOB Experiment Setup

The experimental design selected is a Nearly Orthogonal and Balanced Latin Hypercube (NOB) design by Vieira et al. (2013), which allows a mixture of up to 100 continuous, and up to 200 discrete or categorical factors to be studied, using 512 design points. The design points are distributed nearly uniformly across all dimensions and are nearly orthogonal to each other, meaning the factor effects are unconfounded during analysis.

For this study, one categorical and four continuous factors are varied based on the NOB design. Other input data and model parameters remain fixed throughout the experiment. Simulation runtimes are all kept constant at 1,584 workdays—six years—according to the sponsor work agreement. Figure 14 presents the pairwise plots of all the factor input combinations, and shows the evenly-distributed space-filling behavior produced by the NOB experimental design.

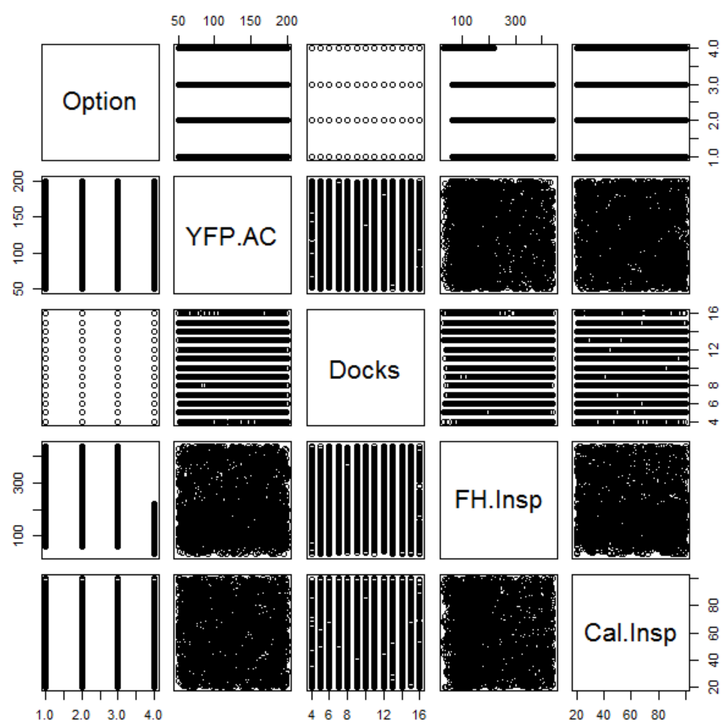


Figure 14. Pairwise Plot of Main Variable Input Factors Showing Factor Space Coverage Achieved with NOB Design Matrix

To improve space filling properties, assignments of factors to columns can be permuted to produce different combinations of the factor settings. The reassignment process is called "rotation," and the resulting values are concatenated to the original design in a process called "stacking." Each design point is further replicated multiple times through the simulation experiment to facilitate assessment of the system's variability. Cioppa and Lucas (2007, p. 54, section 7) conclude that an experimental design of this type provides good space-filling properties and "allows an analyst to examine many factors by fitting a model with main, quadratic and interaction effects with nearly uncorrelated estimates of the regression coefficients for the linear effects terms." These capabilities meet the needs for this study.

Factor settings and ranges used in the design are presented in Table 2. Maintenance policy options are specified by a four-level discrete-valued factor in the spreadsheet, but treated as a categorical factor during the analysis. The design is rotated and stacked 6 times, which results in a total of 6 x 512 = 3,072 design points. Each design point is replicated 30 times. Hence, the overall number of simulated experiments is 92,160.

Table 2. Factors and Factor Space Bounds

Name	**Factor Description**	**Type**	**Interval or {Values}**
Option	Maintenance Policy Option	categorical	{1,2,3,4}
YFP.AC	Yearly Flight Program	continuous	[40,200] FH
Docks	Number of Docks	discrete	[4,20]
FH.Insp	Usage-Based Inspection Turnaround Time	continuous	[66,440] days
Cal.Insp	Calendar-Based Inspection Turnaround Time	continuous	[30,96] days

The four maintenance policy options represent different phase-maintenance policies combining different combinations of usage-based and calendar-based inspection intervals. As described earlier, maintenance policy option 1 is obsolete, and policy option 2 is currently in place. Policy option 3 is a logical extension, but comes with more uncertainty. Policy option 4 is the most ambitious change from the current policy; it may be more difficult to implement, and comes with even greater uncertainty. Due to classification, this cannot be explained further. The ranges for yearly flight plan and the number of docks (maintenance capacity) are determined by the sponsor, and the turnaround time ranges are set after considering the available data and plausible changes that might occur. Note that turnaround time for usage- and calendar-based inspections are fixed values in the model, not parameters of a probability distribution.

4. Conducting the Experiments

Each single simulation run takes about two seconds to execute. Therefore, each single point experiment for time series output and validation purposes, replicated 1000 times, ended up taking about 20 to 30 minutes to run. Actual runtimes are strongly dependent on the volume of output data to be written into the CSV file. For NOB input design analysis, 3072 design points were replicated 30 times, resulting into a runtime of about 38.5 hours on a standard laptop.

IV. RESULTS

This chapter summarizes results obtained from the simulation study described in Chapters II and III. In addition to the use of a reliable simulation tool for fleet management that has been delivered to the German Army for use in practice, these results offer important practical insights. The following sections describe the results of the model validation process, followed by a presentation of results that answer the study questions posed in Chapter I.

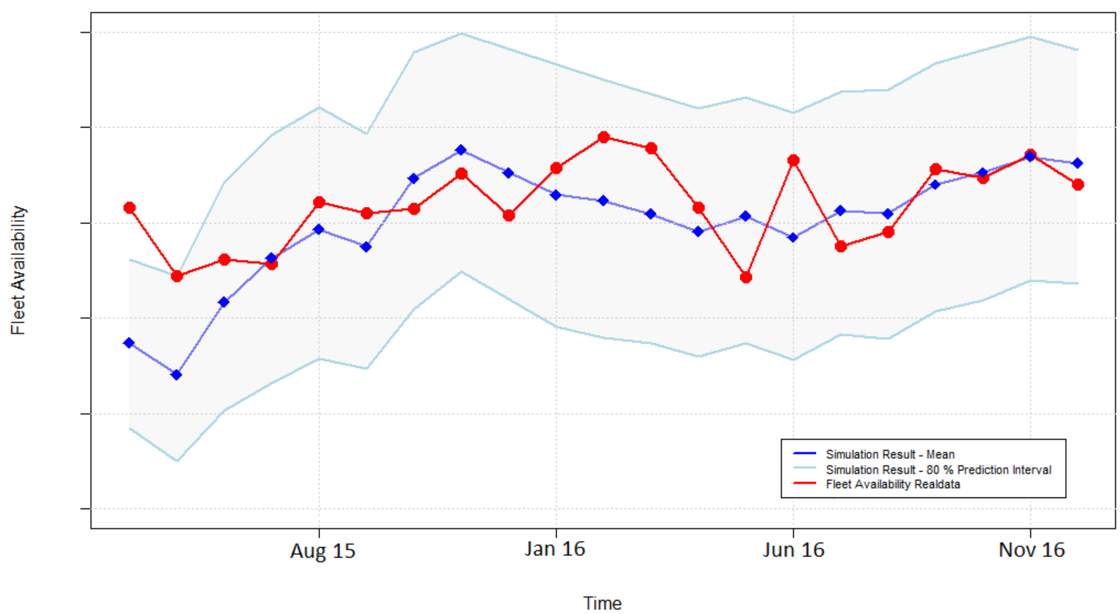
A. MODEL VALIDATION

1. Overview

Law (2015) defined validation as "the process of determining whether a simulation model is an accurate representation of the system described, for the particular objectives of the study" (p. 247, Chapter 5). In other words, if actual data exist, the simulation output generated on the basis of defined input factor changes should be comparable to those same changes having been made in the system as used in practice. To achieve validation, input-factor probability distributions should accurately reflect actual fleet data in the model. Our measures of effectiveness (MOE) defined in Chapter II, Section E were selected following conversations with subject-matter experts in the German Army. For the model validation process, two techniques are used: (1) comparison of simulation output with data from the actual system, and (2) sensitivity analysis, which demonstrates response of the model to defined changes in input variables. Results for both techniques are presented below.

2. Comparison with the Existing System

Law (2015) states that "the most definitive test of a simulation model's validity is to establish that its output data closely resembles the output data that would be expected from the actual system" (p. 262, para 5.4.5). We use a validation period that spans the dates 1 April 2015 to 31 December 2016 in agreement with the sponsor. Actual fleet availability data is provided as time series data for each month, which we compare to output from the model simulated 1000 times. The corresponding outcome for each simulated workday is summarized as a daily mean as well as lower and upper deciles. These deciles may be used as an 80% prediction interval about the mean curve. The time-series data is then averaged on a monthly basis for comparison with the delivered real fleet availability data. In agreement with the sponsor, the goal of the validation process is to achieve a mean deviation of simulated results from the given real fleet availability data (mean absolute error) below 5%. Figure 15 presents the plot showing the final model validation result for fleet availability rate, which achieves an error of 4.3%.

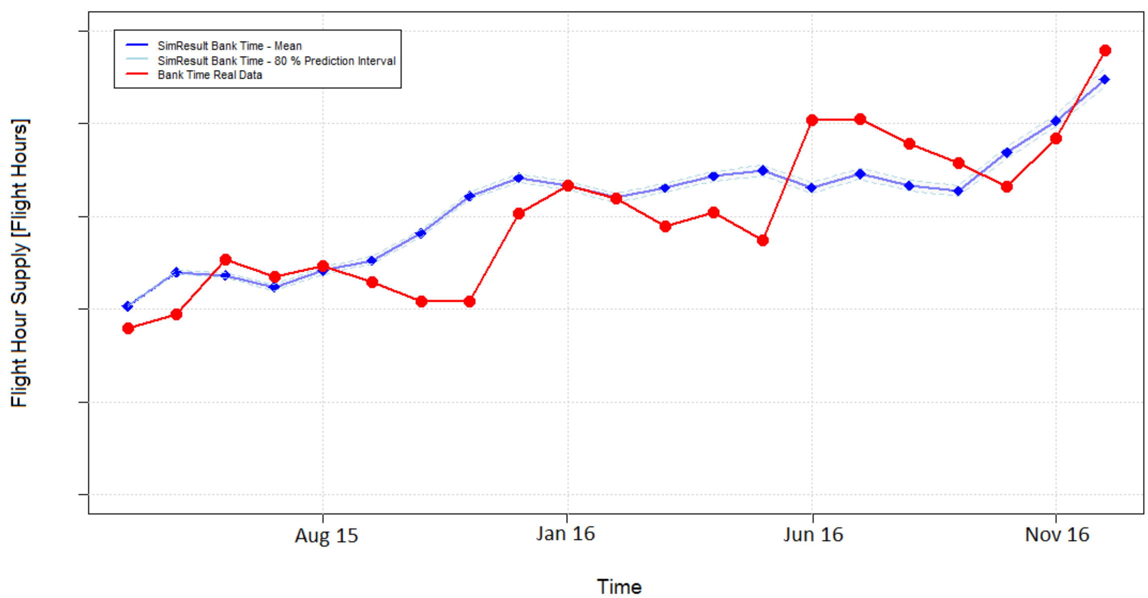


Real fleet availability data is shown in red and simulated data is shown in blue. The shaded area represents the 80% prediction interval. Mean absolute error ε = 4.3%.

Figure 15. Validation Results for Availability Rate from Period April 1, 2015–Dec. 31, 2016

Figure 15 also shows that roughly half of the simulated monthly average availability values are below the curve and the other half are either on or above the real data curve, which supports the argument of a reasonable model fit.

Figure 16 presents the plot showing the final model validation result for flight hour supply. Again, achieved results strongly indicate a suitable response fit with respect to the flight hour supply for the implemented model. The mean absolute error concludes to 1.3%.



Real flight hour supply data is shown in red and simulated data is shown in blue. The shaded area represents the 80% prediction interval. Mean absolute error ε = 1.3%.

Figure 16. Validation Results for Flight Hour Supply (Bank Time) from Period April 1, 2015–Dec. 31, 2016

3. Sensitivity Analysis

Although a successful comparison with the existing system supports belief in the validity of the model, sensitivity analysis is used to check that the simulation model responds as anticipated to changes in inputs. In Figure 17 we present the results of a sensitivity analysis involving several factors. The perturbed factors are increases and decreases in inspection turnaround time of

40%; increasing the special inspection occurrence probability threshold by 50% and then setting the probability threshold to zero; and a 100% increase (doubling) in average MTBF. Due to classification of achieved analysis results, base levels of perturbation factors are not published. Obviously, one expects fleet availability to increase with a decrease in non-recurring special inspection frequency, and turnaround times such as an increase in MTBF would affect availability. A decrease in availability is assumed for the opposite cases, respectively. As can be observed in Figure 17 and Figure 18, the model does respond exactly as it is supposed to do. Without being more specific, the mean error is increasing with the presented factor changes.

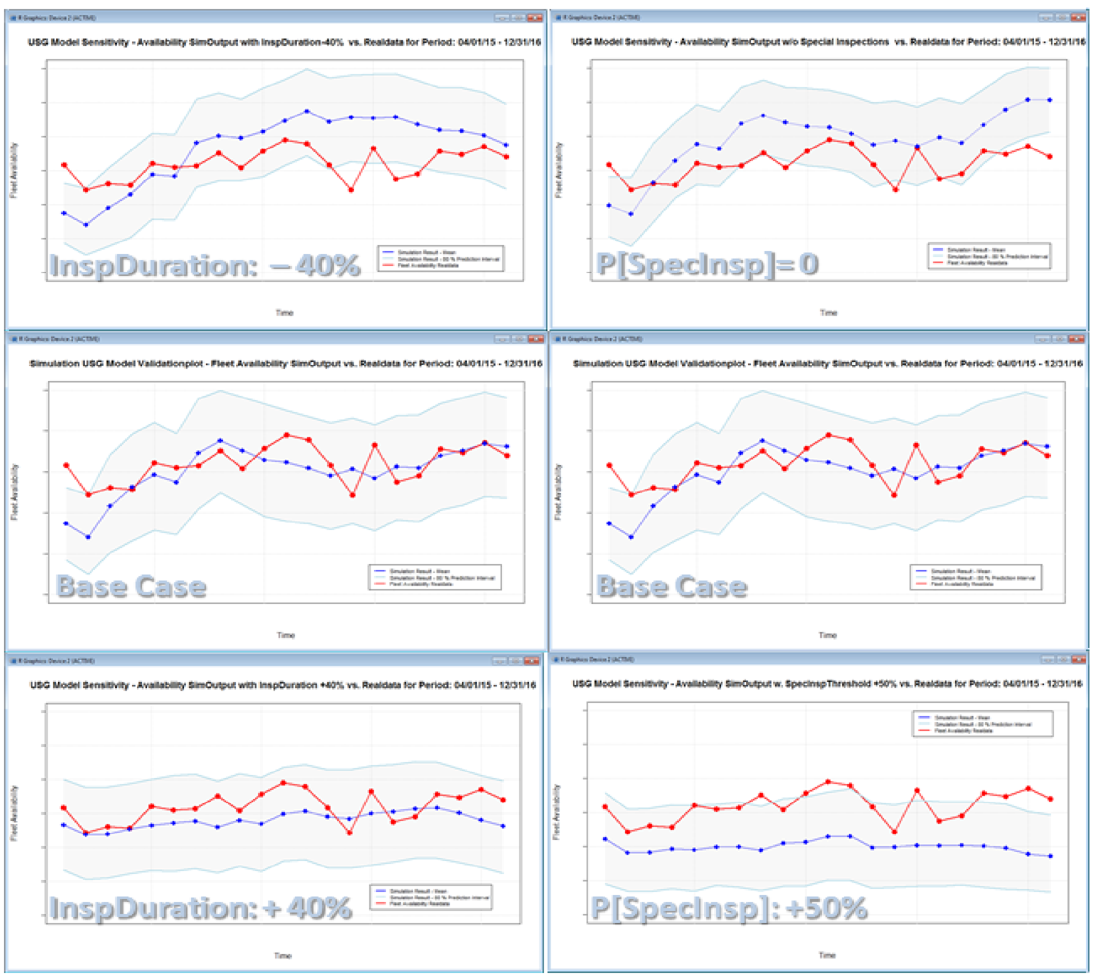


Figure 17. Sensitivity Analysis for Inspection Turnaround Times and P[SpecInsp])

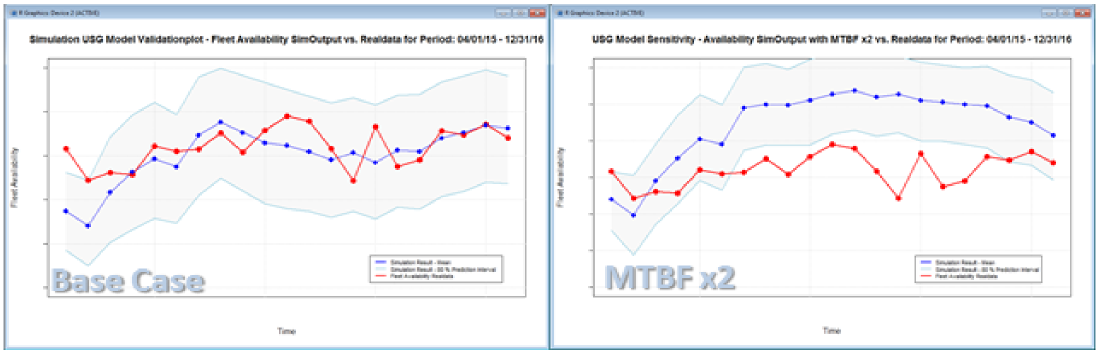


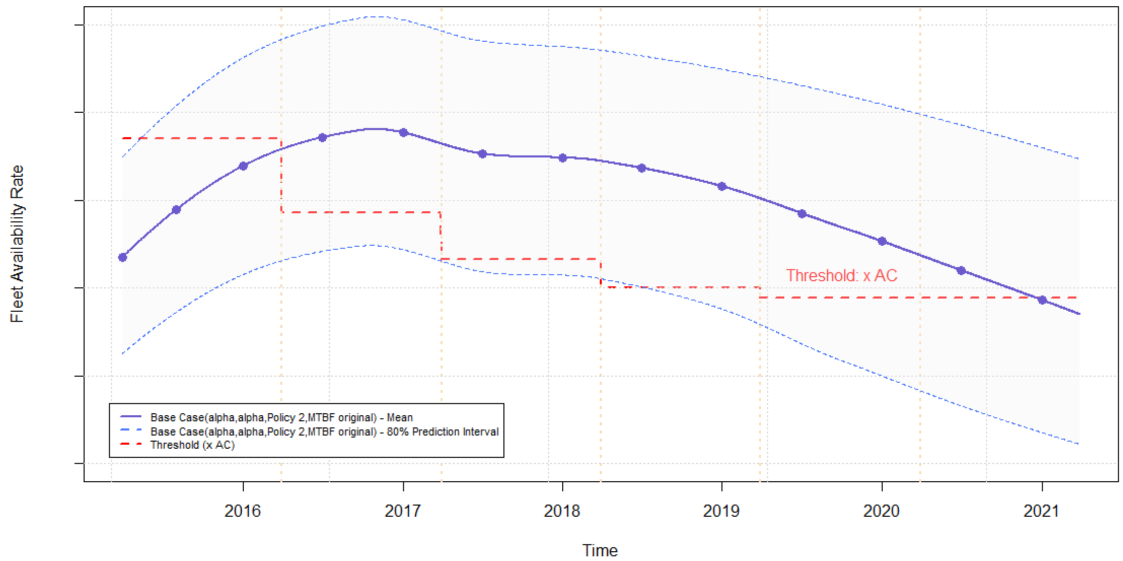
Figure 18. Sensitivity Analysis for MTBF

Also, changes in the relative positions of the simulated outcome to the real data are arising as anticipated.

B. TIME SERIES RESULTS

1. Base Case Analysis

The simulation input parameter setup representing actual fleet conditions constitutes the base case. The base case, defined by maintenance policy 2 which is the currently applied inspection system, and factor levels gained from data analysis, has fleet utilization at 80 flight hours per aircraft per year, and an increasing number of total flight hours for the fleet due to an increasing fleet size over the years. A six-year period, starting on 1 April 2015, is defined as a plausible time span for simulation analysis of fleet dynamics. This includes the known fleet condition at $\mathbf{t_0}$ (aircraft information including delivery dates, age, reliability parameters and inspection information), the validation time period (528 simulated workdays representing period 1 April 2015 until 31 December 2016), the aircraft procurement cycle, and about three additional years to reach the final fleet size. Figures 19 and 20 present simulated time series results for availability rate and availability gap in the base case scenario.



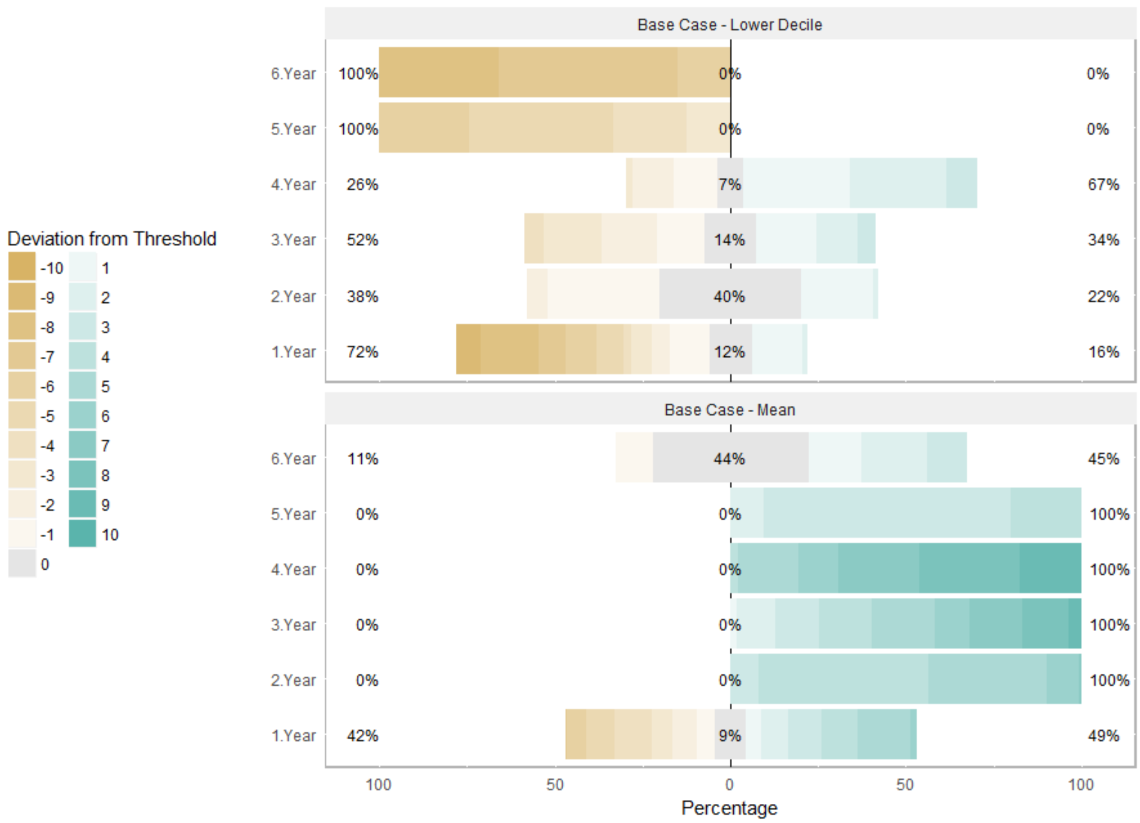
Given single-point time series results for availability rate reflect on base case scenario at 80 flight hours per aircraft and year and applied maintenance policy 2 (inspection system variant 2). Inspection Duration and Maintenance Capacity are at mean level derived from given fleet live data.

Figure 19. Base Case Simulation Results with 80% Prediction Interval for Fleet Availability Rate and Readiness Threshold Adapted to the Change in Fleet Size

Longer simulation time frames may be used, but at a loss of realism due to unforeseeable circumstances such as changes in fleet management, aircraft design, and reliability of components. Figure 19 shows that maximum availability is reached at the end of 2016, with a significant downward trend in fleet availability over the following years, which is dominating the positive effect of fresh aircraft deliveries. But more interestingly, the prediction interval reveals a significant probability of falling below the given threshold of 10 daily serviceable aircraft across nearly the whole period. More precisely, beginning in the second quarter of 2018, there is a significantly growing probability of sustainably falling below the given threshold. This metric refers to research question six imposed by the sponsor and defined in Chapter I.

The Likert divergent bar chart presented in Figure 20 gives more detail on the magnitude of deviations from the threshold or availability gap as one of the

MOEs over the time frame simulated. It shows the proportion of workdays on which the number of serviceable aircraft is below (brown), exactly at (grey) or above (blue shadings) the given threshold of 10 serviceable aircraft separately for each year in the simulation. The zero-line in the middle of the plot represents the threshold provided, and the scaled shadings on each side represent the exact deviation or availability gap. Overall, performance and trends can be identified very easily with this visualization.



This Likert plot shows lower decile and mean for number of aircraft serviceable for flight missions normalized on the given threshold of 10 aircraft, which is represented by the zero–line dividing both sides in the plots. Brown is below, grey exactly at, and blue above the threshold. Shading represents the actual differences according to the given legend.

Figure 20. Likert Divergent Bar Chart for Base Case

For example: while on average (base case mean) the number of aircraft serviceable for flight operations only falls below the given threshold on about

11% of all workdays in 2021 which is the sixth year of the simulation; there is a 10% chance that this number is below the threshold 100% of the time in the last two years (base case lower decile). The lower decile implies that there is a 90% chance that the number of aircraft actual serviceable for flight operations deviates from the threshold of 10 aircraft at least in the presented proportion of workdays. The lower and upper deciles provide 80% prediction bounds on availability at any given time for the scenario under consideration. In addition, the bar chart in Figure 21 gives a summary of the average fleet condition by year, which also provides insight into fleet availability trending over time. The chart shows the average distribution of fleet condition per simulated year according to the defined status groups. Again, percentages are not published.

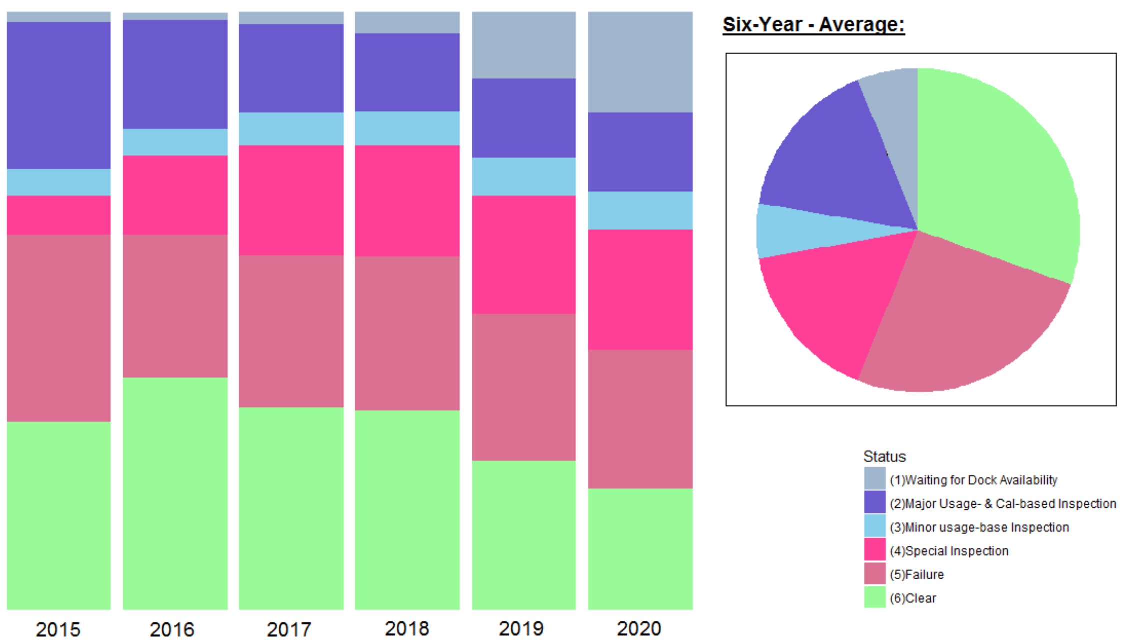
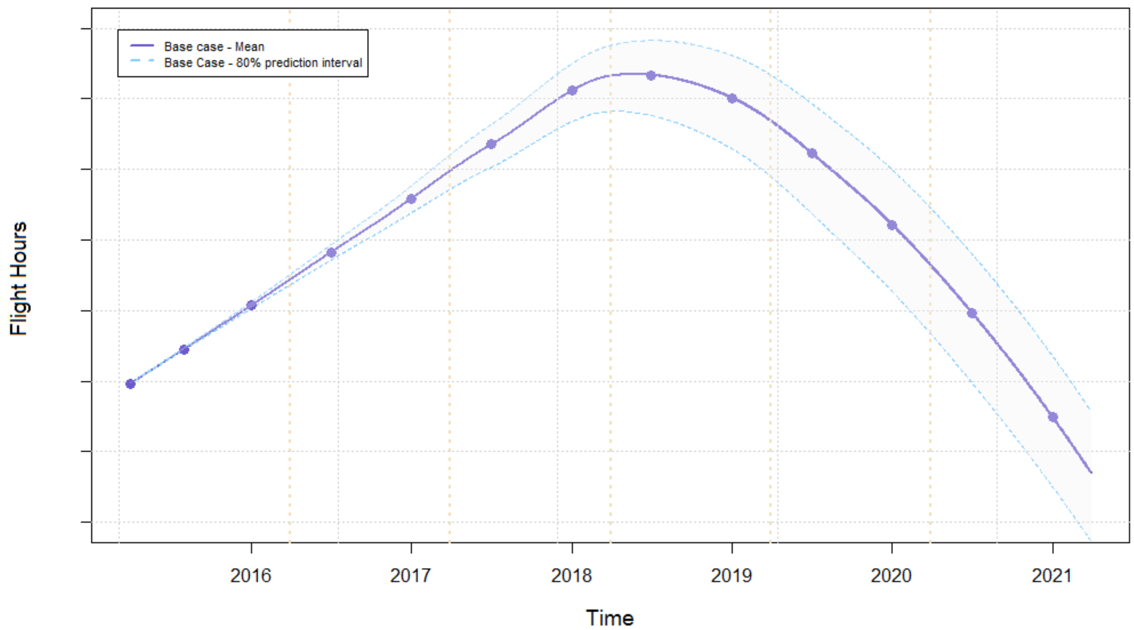


Figure 21. Stacked Bar-Chart for Fleet Condition over Time with Overall Mean for the Six-Year Period Displayed in the Pie Chart

The percentage of aircraft serviceable for flight operations (green) is decreasing over time due to an increasing number of non-recurring special inspections (red) and an increasing number of aircraft waiting in queue for available phase maintenance (dock) capacity (grey). A high percentage of aircraft in failure repair (brown) reveals that insufficient aircraft reliability, non-recurring special inspection events, and major phase inspection can easily be identified as main drivers for lack of availability. A growing queue of aircraft waiting for maintenance (grey) determines the negative trend in availability.

On average, with the negative trend in availability over time shown in Figures 19 and 21, the base case scenario shows a shortfall in the number of available aircrafts on about 65% of simulated workdays across the simulated time frame with reference to Figure 20. These outcomes provide estimates of average future fleet availability under the assumption that current policies and fleet conditions remain in place. These results imply growing challenges with respect to fleet availability in the near future, if the situation stays as is.

In addition, Figure 22 shows that flight hour supply also shows a sharp downward trend after reaching a maximum in 2018. The upward trend that is seen in flight hour supply before it reaches its maximum is illusory, the result of new aircraft being delivered to the fleet.



Given single point time series results for flight hour supply reflect on base case scenario at 80 flight hours per aircraft and year and applied maintenance policy 2 (inspection system variant 2). Inspection Duration and Maintenance Capacity are at mean level derived from given fleet live data.

Figure 22. Flight Hour Supply Development for Total Fleet Over Simulated Time Frame

Once aircraft delivery is concluded, the supply of flight hours cannot keep pace with demand due to long maintenance turnaround times and the relatively large number of calendar-based inspections, which do not produce flight hours. As more reliable aircraft carry the load of the failure-prone aircraft, flight-hour based preventive maintenance schedules for the former are accelerated. The queue of aircraft waiting for maintenance grows over time as maintenance assets become strained. Because flight hour production is not keeping up with fleet utilization due to constant demand, flight hour supply of the fleet is degrading. Together with a growing queue, this implicates insufficient maintenance capacity or over-utilization of the fleet.

2. Response Surface Metamodeling and Analysis

Construction of a statistical metamodel that describes the relationship between input factors and the output response is a common end product of running a simulation experiment. Multidimensional linear or logistic regression models are often used. We start by loading the output CSV-file into an *R* data frame. Please note, once again, that some inputs like failure repair times, minor usage-based inspection duration, and special inspection turnaround times come from bootstrapped data that remain unchanged throughout the experiments. Also, the special inspection threshold and Weibull failure parameters for aircraft failure behavior remain constant throughout the experiments. Because they are easily changeable via code and fleet input CSV-files, respectively, they could also be made available for CSV-based automated input as additional study factors, but this is a subject for future work. Also, simulation run lengths are held constant at 1,584 work days for each experiment. Four factors or predictor variables remain for further analysis in this study.

Prior to regression analysis, the complete data set is separated into four subsets, one subset for each maintenance policy. The remaining four input factors (yearly flight hours per aircraft, maintenance capacity and the two major inspection turnaround times) are used as predictor variables in linear regression using the *lm* method in *R*. Response variables under evaluation are availability rate, flight hour supply, mission completion, and dock utilization. The regression model fit procedure itself is done in several steps. As a start, the most simplistic model possible, containing only raw predictors, is used to build a preliminary fit. This first model fit is then used in a stepwise procedure realized with the *step* function in *R*, allowing quadratic effects and second-order interaction terms. The step function evaluates possible predictor and interaction term combinations with respect to the resulting Akaike Information Criterion (AIC). Finally, the corresponding optimal model fit recommended by *step* chosen with respect to a minimized AIC value is created. The analyst often uses judgment to refine the model further until a suitable model is available for further analysis.

3. Fleet Availability Regression Analysis

Fleet availability is considered the most important response variable, and is defined as the ratio of serviceable aircraft to fleet size. Since this is always a value between zero and one, a log-odds transformation seems appropriate.

$$y = \log \frac{ARate}{1-ARate} \tag{8}$$

As can be observed in Figure 23, the first simple linear regression without transformations and interaction terms in the first iteration revealed significant non-linear curvature in the partial residual plots, heteroscedasticity, and an R-squared value of 0.731.

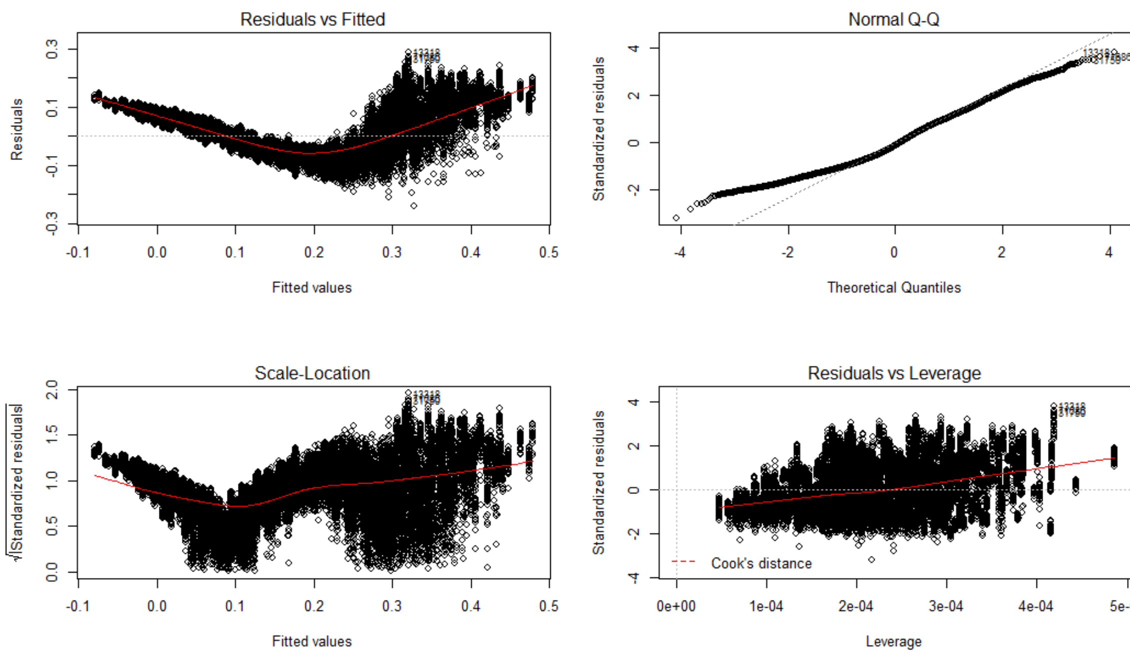


Figure 23. Residual plots of Simple Regression Model Fit of First Iteration for Fleet Availability Rate.

Residual plots created with *termplot* also show a poor model fit for yearly flight hours per aircraft. After applying the *step* function in *R* for stepwise finding a suitable fit, the logit transformation is used to transform the response variable, which increased the R-squared to 0.873. Still, the model lacks fit. By looking at the partial residual plots of each predictor generated by the *termplot* function, an inverse transformation is indicated for the planned yearly fleet utilization (YFP.AC) predictor, which represents yearly flight hours per aircraft. The partial residual plot is presented in Figure 24. Inverse transformation is done by adding an artificial column with the inverted utilization values to the existing data frame, which then is used as a predictor in the regression model. For deriving predictions later on, this has to be recognized in the prediction data. In the third and final iteration, the YFP.AC variable is manipulated with an inverse transformation by using a new data column yielding the inverse values of YFP.AC in the regression model derived in the second iteration.

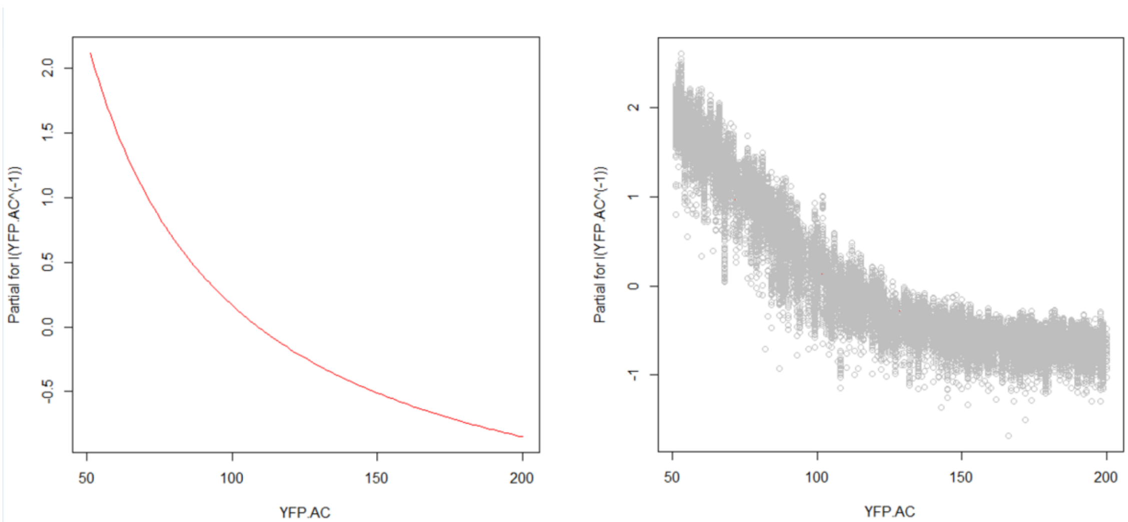


Figure 24. Partial Residual Plot of YFP.AC Predictor Variable

The resulting final model produces a reasonable fit, which covers 93.7% of the variability (Figures 25 and 26).

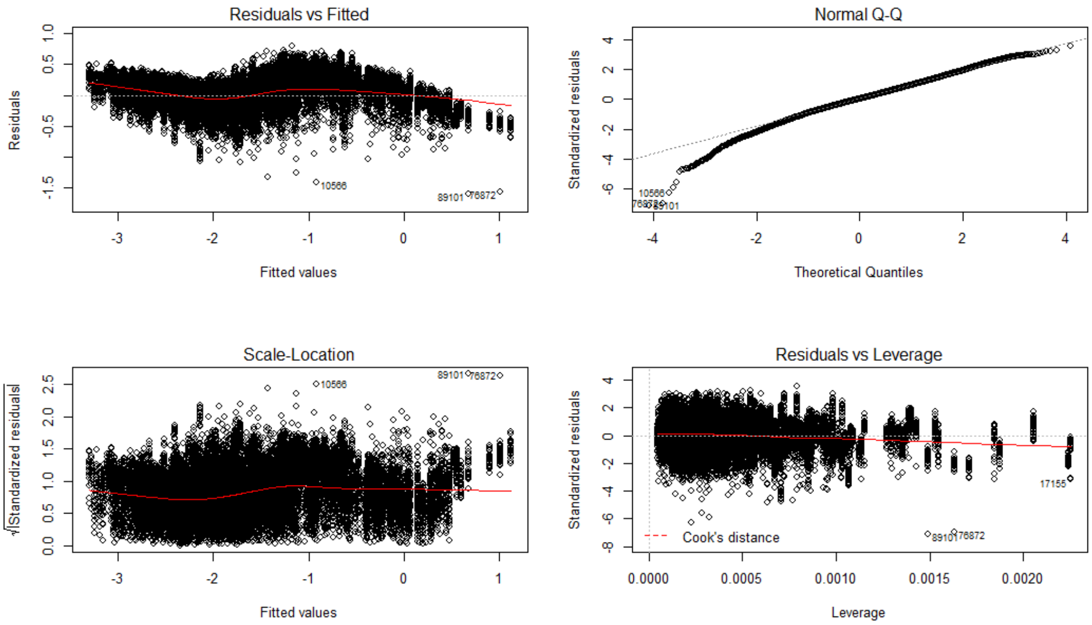


Figure 25. Residual Plots of Final Iteration with all Transformations for Model of Fleet Availability

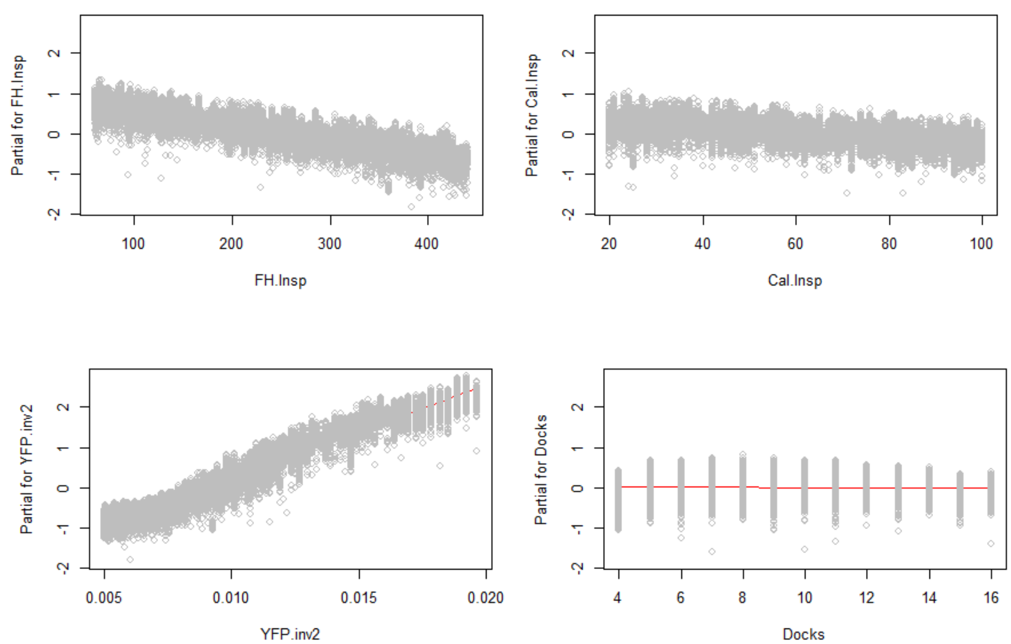


Figure 26. Partial Residual Plots of Final Iteration with All Transformations for Final Fleet Availability

The residual plots and partial residual plots look much better, as can be observed in Figures 23 and 24. A summary of the final regression model fit is presented in Table 3, showing p-values of all integrated predictors, interaction terms and the overall R-squared and p-value representing the quality of the fit. Equation 9 represents the corresponding metamodel for availability rate with transformations:

$$ARate = \frac{e^{\eta}}{1+e^{\eta}} \tag{9}$$

with

$$\eta = b + \frac{c_1}{YFP.AC} + c_2 FH.Insp + c_3 Cal.Insp + c_4 \frac{FH.Insp}{YFP.AC} + c_5 \frac{Cal.Insp}{YFP.AC} \tag{10}$$

$$+ c_6 FH.Insp * n_{Docks} + c_7 Cal.Insp * n_{Docks} + c_8 FH.Insp * Cal.Insp$$

Table 3. R-summary of Final Logistic Regression Model Fit with Factors, Interactions, and Their Corresponding p-values

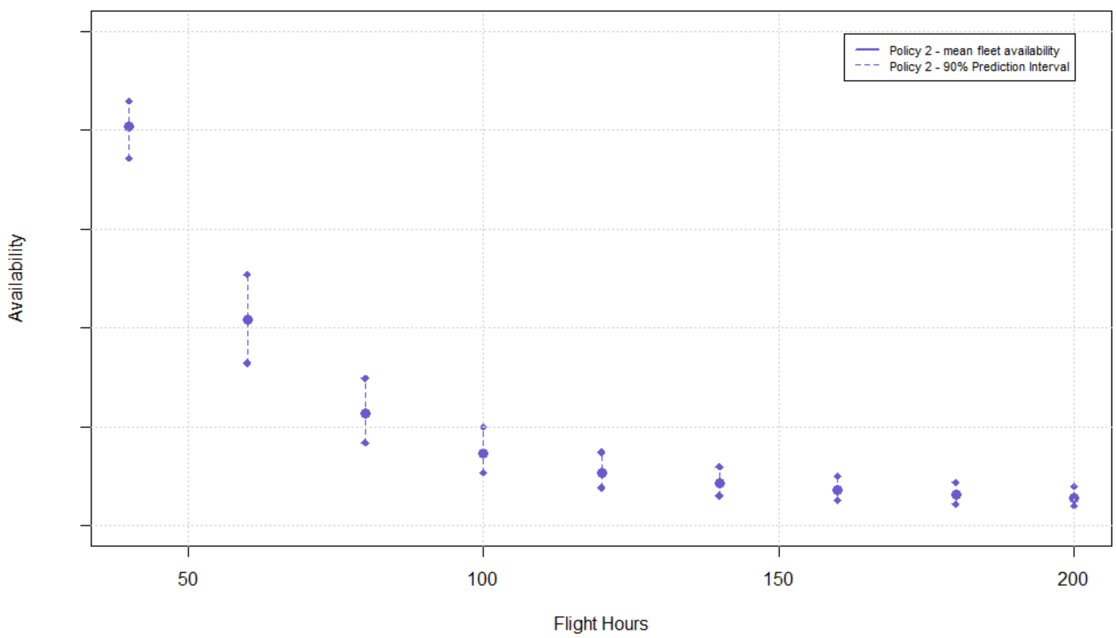
```
Call:
lm(formula = log(ARate.mu/(1 - ARate.mu)) ~ YFP.inv2 + FH.Insp +
    Cal.Insp + YFP.inv2:FH.Insp + YFP.inv2:Cal.Insp + Docks:FH.Insp +
    Docks:Cal.Insp + FH.Insp:Cal.Insp, data = USG_test.02)

Residuals:
     Min       1Q   Median       3Q      Max
-1.59987 -0.13332  0.00818  0.14665  0.80811

Coefficients:
                    Estimate Std. Error  t value Pr(>|t|)
(Intercept)       -3.054e+00  1.634e-02 -186.875  < 2e-16 ***
YFP.inv2           2.359e+02  1.334e+00  176.856  < 2e-16 ***
FH.Insp           -3.612e-03  5.667e-05  -63.739  < 2e-16 ***
Cal.Insp          -6.783e-03  2.589e-04  -26.202  < 2e-16 ***
YFP.inv2:FH.Insp   2.133e-02  3.338e-03    6.391 1.68e-10 ***
YFP.inv2:Cal.Insp -6.111e-01  1.653e-02  -36.967  < 2e-16 ***
FH.Insp:Docks      1.041e-04  2.918e-06   35.663  < 2e-16 ***
Cal.Insp:Docks     6.003e-04  1.213e-05   49.504  < 2e-16 ***
FH.Insp:Cal.Insp   7.126e-06  5.634e-07   12.647  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2262 on 22821 degrees of freedom
Multiple R-squared:  0.9369,    Adjusted R-squared:  0.9369
F-statistic: 4.235e+04 on 8 and 22821 DF,  p-value: < 2.2e-16
```

The model fit of fleet availability rate presented above is shown as a representative example for all other regression model fitting procedures used throughout this study. Although the same approach is used for all four response variables under review, different variable transformations may apply. The ultimate advantage of using a NOB design is its capability to generate data that can be examined in many different ways. For example, it offers opportunities to produce a variety of plots and analyses containing much more information than just response behavior over time, without conducting numerous additional simulation experiments. If the number of factors is large, an efficient experiment such as a NOB may be the only way of simultaneously studying the factors in a reasonable amount of time.

In this study with only a small number of factors, an alternative to the NOB would be a full factorial (or gridded) design with a small number of levels for each quantitative factor. For example, a design that includes all combinations of the five levels for each of the four quantitative factors and four policy options requires 2500 design points. The NOB is used because it allows the same size design to be used even if the number of factors is much larger—in this case, 512 design points to investigate up to 300 factors. A factorial design becomes impractical very quickly. If we wished to study even ten quantitative factors at five levels, along with the four policy options, that would require over 39 million design points.

Once metamodels have been fit to the output data from a designed experiment, graphs can be more powerful ways of revealing the metamodels' behavior. Figures 27 and 28 illustrate the metamodel results of Equations (9) and (10) for specific variants of the base case scenario (maintenance policy 2). These figures show fleet availability rate and mission completion rate as a function of yearly utilization per aircraft. With all other input parameters remaining unchanged, results of the simulation indicate a nonlinear decline in fleet availability with an increase in planned fleet utilization. This agrees with the sensitivity analysis in Section C below. These graphs also make it easy to evaluate fleet performance under the assumption of different levels of planned fleet utilization. Given a specific threshold of planned fleet utilization, the corresponding fleet availability can directly be read from the graph as a function of planned utilization or the other way around.

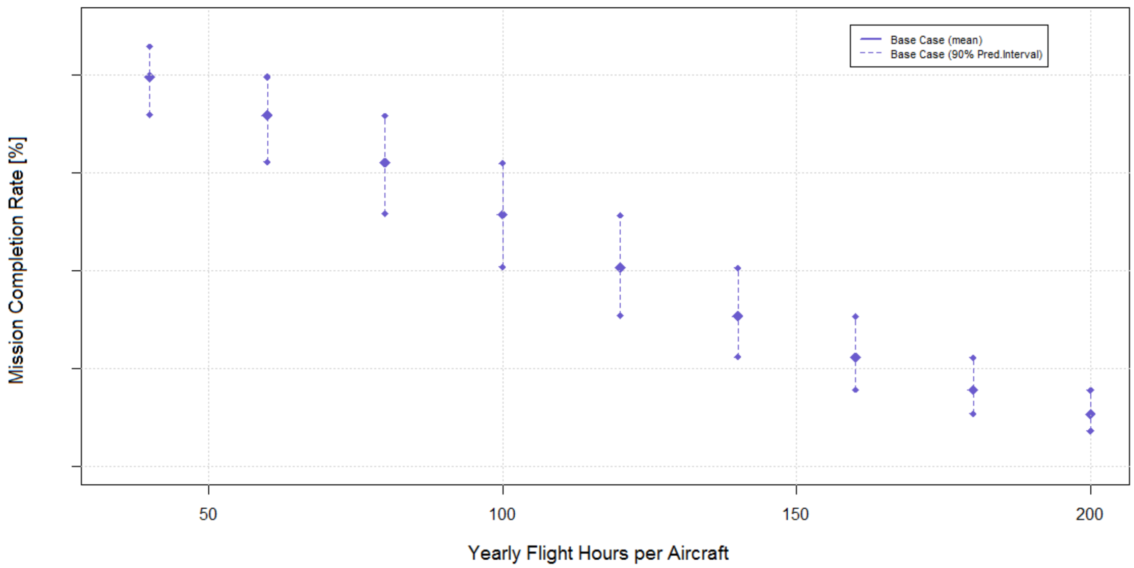
Another benefit of metamodeling is that graphs such as those in Figures 27 and 28 can be constructed in a tiny fraction of the time it would take to make new simulation runs. Simulation runtime for the nine points presented in Figure 27 with the corresponding replications alone would take about three hours of simulation and data preparation on a standard machine, but the metamodel evaluations required to make the graph take only seconds. In our study, effort is focused on finding ways to achieve a sustainably optimized fleet availability and flight hour supply over the span of the simulated period.



NOB design results presented are based on the four-year mean fleet availability for time period 01/01/17 – 03/31/21, derived from approximately 23,000 simulation runs. The NOB design matrix contained six rotations with 30 replications each. Results shown are mean and 90% prediction interval for fleet availability rate in % derived by utilizing the *predict*- function in *R*.

Figure 27. NOB Result for Base Case Scenario—Availability Rate over Fleet Utilization (Yearly Flight Hours per Aircraft)

That especially includes finding a possible solution for trend reversion in availability and flight hour supply. Base-case results for mission completion as a performance metric are shown in Figure 28. It is easy to observe how mission completion, which is the proportion of flight hours actually completed in flight missions to the total demand in flight hours, declines with increasing fleet utilization.



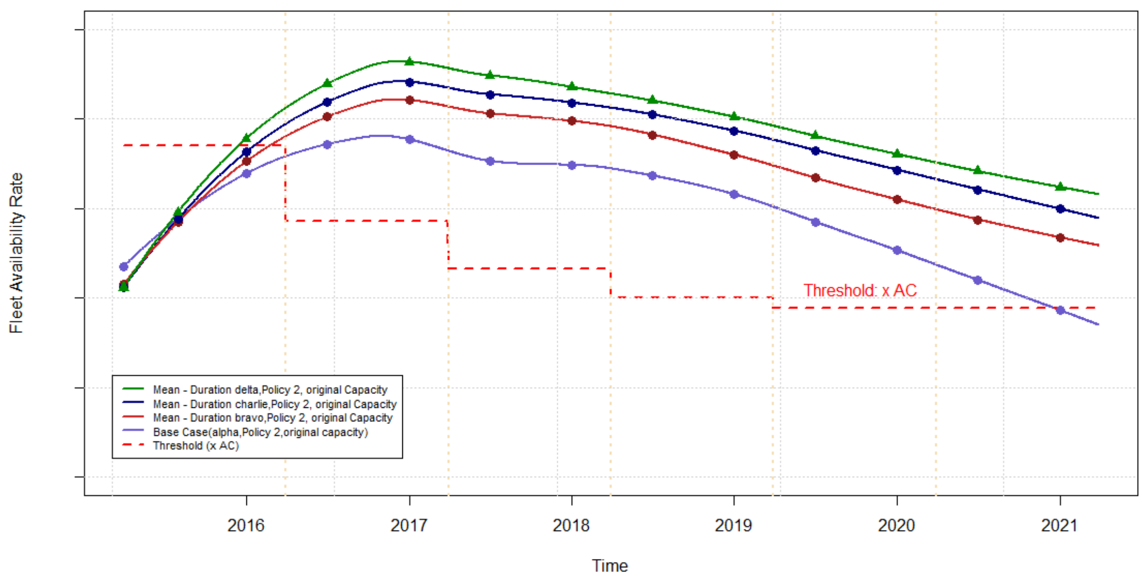
NOB design results presented are based on the four-year mean mission completion rate for time period 01/01/17 – 03/31/21, derived from roughly 23,000 unique simulation runs. The NOB Design matrix contained six rotations with 30 replications each. Results shown are mean and 90% prediction interval for mission completion rate in % derived by utilizing the *predict-* function in *R*.

Figure 28. NOLH Result for Base Case Scenario—Mission Completion Rate over Fleet Utilization (Yearly Flight Hours per Aircraft)

Flight hours lost due to failures and the number of downed aircraft increase with utilization. Referring to research question 2, the defined threshold for mission completion for the fleet in practice given by fleet management is 80%. Although the outcome values cannot be published at this point, the maximum planned utilization metric compliant to this guideline is easy to derive from the plot in Figure 28. It is easy to see, if achievement of this level of performance is realistic under the given factor combination, or not. We discuss this in the following subsection.

4. Inspection Duration Analysis

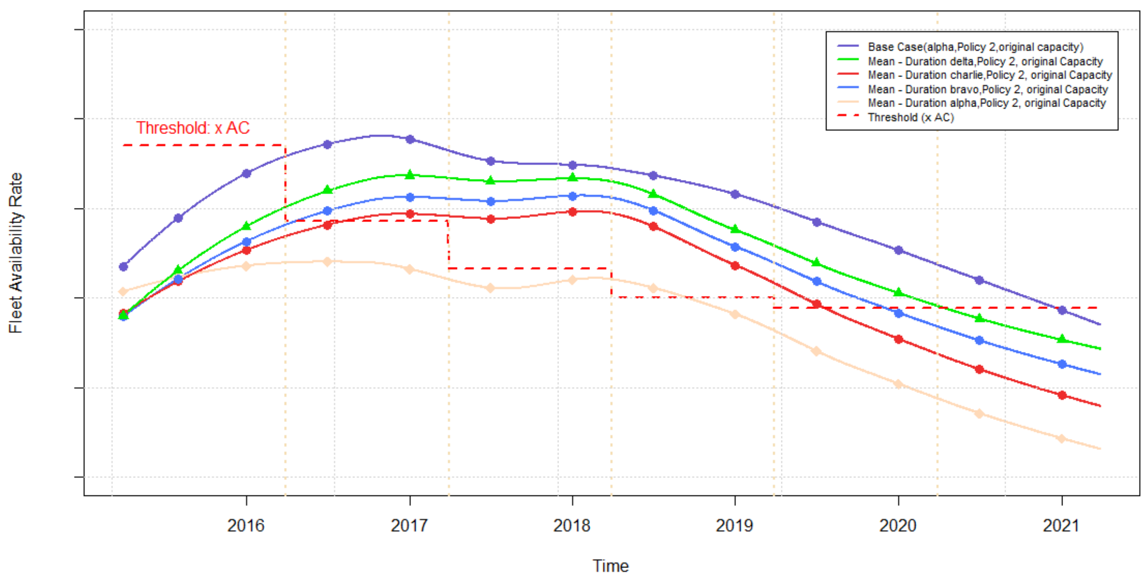
The turnaround time to perform a major phase maintenance inspection is an important determinant of availability. In addition to the base case scenario at 80 flight hours per aircraft per year including the current mean inspection duration (for usage-based inspections only) derived from fleet data, two other levels of interest provided by the sponsor are used in simulations of our model, each of which represents a reduction in turnaround times. Figures 29 and 30 present results for conducting inspections at 80 and 100 yearly flight hours per aircraft, respectively.



Single point time series results shown present availability rate as function of time for inspection. Duration variations relative to base case level of turn-around times at planned fleet utilization of 80 flight hours. Level alpha: -30%, Level bravo: -40%, Level Charlie: -60%, Level delta: -70%. Maintenance capacity alpha represents base case capacity given by fleet live data

Figure 29. Changes in Fleet Availability over Time for Different Inspection Turnaround Times of Major Usage-based Inspections at 80 Flight Hours per Aircraft and Year

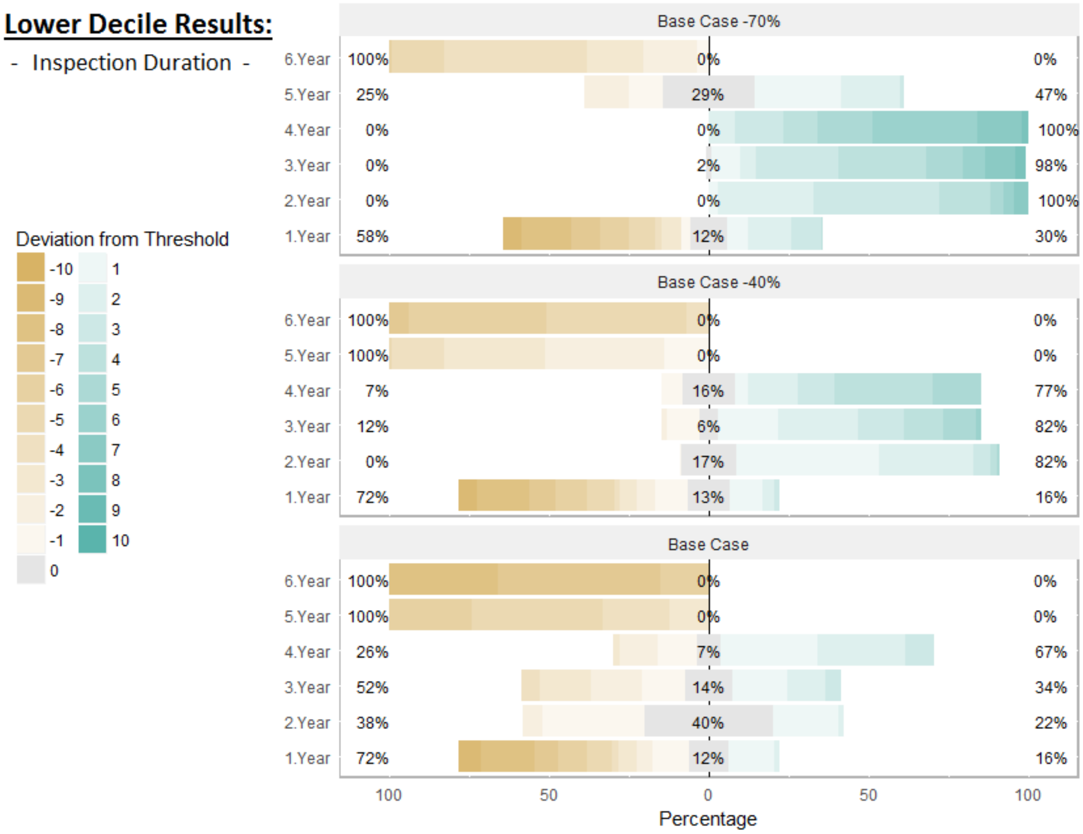
These results are based on single point time series experiments. Not surprisingly, a decrease in inspection turnaround times improves the average fleet availability, but it is of interest to note that a pattern of declining availability past 2017 still occurs under each of the reduction scenarios considered. This finding suggests that significant changes to the system are needed, such as fundamental changes in maintenance policy, increased capacity, substantial reduction in repair times, or improved aircraft reliability. These trends become worse with increasing fleet utilization.



Single point time series results shown present availability rate as function of time for inspection Duration variations relative to base case level of turn-around times, at planned fleet utilization of 100 flight hours. Level alpha: -30%, Level bravo: -40%, Level Charlie: -60%, Level delta: -70%. Maintenance capacity alpha represents base case capacity given by fleet live data

Figure 30. Changes in Fleet Availability over Time for Different Inspection Turnaround times at 100 Flight Hours per Aircraft

In Figure 30, all scenarios provide an inferior fleet performance relative to the base case at 100 yearly flight hours per aircraft. As noted above, improving inspection turnaround times alone is not sufficient to achieve stable fleet performance at a satisfactory level of availability. The Likert divergent stacked bar chart in Figure 31 illustrates how the frequency of threshold violations declines over the years with decreasing inspection turnaround times. Presented is the lower decile for each case. This means that there is a 90% chance that results predicted by the model will occur at least at the levels shown in reality.



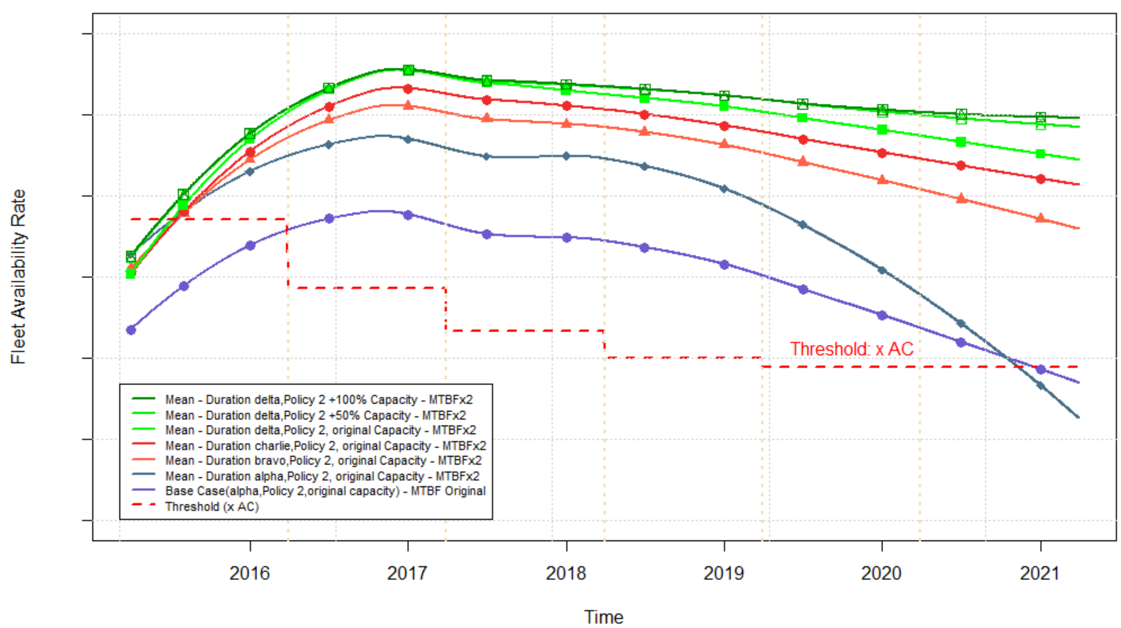
This Likert plot shows lower decile for number of aircraft serviceable for flight missions normalized on the given threshold of 10 aircraft, which is represented by the zero – line dividing both sides in the plots. Brown is below, grey exactly at, and blue above threshold. Shading represents the actual differences according to the given legend.

Figure 31. Likert Plot of Deviation from Threshold for Number of Serviceable Aircrafts (Base Case and Base Case Variations with Respect to Inspection Duration)

Percentages on the blue side (days with more than 10 serviceable aircrafts) significantly increase over the years, while percentages on the brown side (threshold violations) decrease simultaneously. Although threshold violations decrease over time, even in the best-case scenario there is a significant number of violations especially in the sixth year (2021). This effect is due to the decreasing trend observable in the time series plots in Figures 19, 29, and 30. Therefore, even though turnaround time is a factor that drives fleet dynamics, improving it in isolation is not sufficient to deliver satisfying results.

5. Reliability Analysis

Because tolerating a large reduction in fleet utilization is not an acceptable option, we examine the effects of changes made to maintenance policy, capacity and aircraft reliability. The simulation results presented in Figures 32 and 33 are produced under the assumption that the mean time between failure (MTBF) is twice as large as estimates derived from the current fleet data.

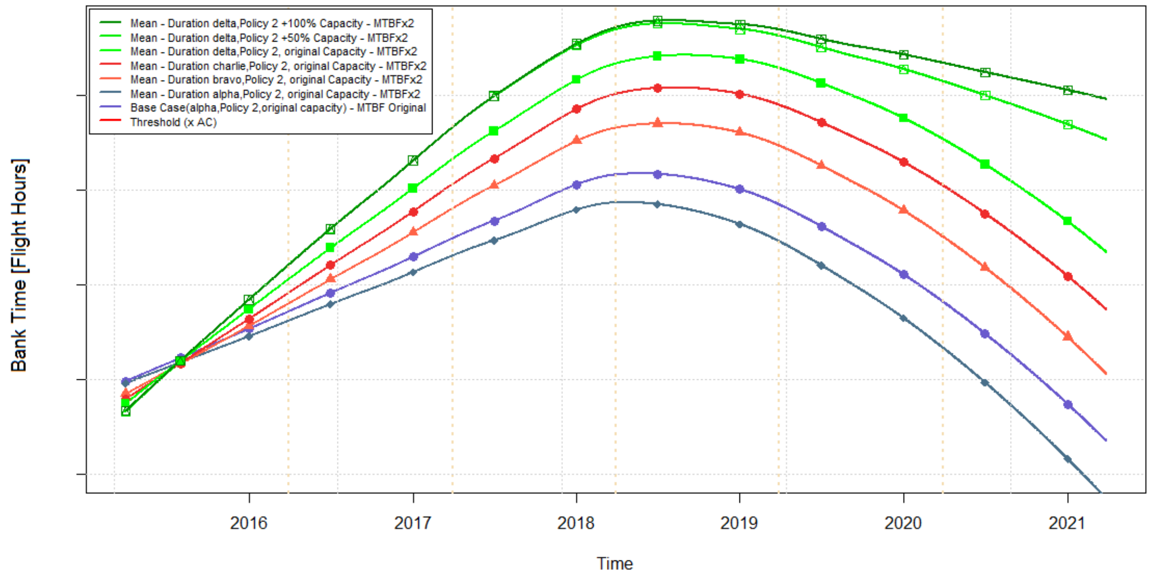


Single point time series results shown present availability rate as function of time for inspection Duration variants relative to base case at planned yearly fleet utilization of 80 flight hours per aircraft. Inspection duration - alpha: -30%, bravo: -40%, Charlie: -60%, delta: -70%. Aircraft reliability is doubled (MTBF x2).

Figure 32. Changes in Fleet Availability over Time for Different Inspection Turnaround Times and MTBF Improved by a Factor of 2

The impact of maintenance policy and capacity on fleet performance is treated in the NOB section (Section C of this chapter). Technical measures such as software updates, improvement of components over time, or progress along the learning curve of personnel, are ways to improve aircraft reliability in the future. Figures 32 and 33 show the corresponding model response on availability and flight hour supply in time-series representations. Although it is generally the case that improvement in aircraft reliability leads to improvement in fleet availability, the direct comparison of fleet availability shown in Figure 32 reveals interesting behavior. A reduction of inspection turnaround time of about 30% in principle does not prevent the negative trend from appearing, although fleet availability is improved on average; 10% more effort does the job much better. With a reduction of 40% in turnaround time, fleet availability improves even more and, more importantly, the trend loses momentum quickly. Therefore, the recommendation implied by these simulation results is the following: reduction of inspection turnaround time by at least 60% together with an improvement in aircraft reliability by a factor of 2. Additional maintenance capacity seems to support positive effects even more. Figure 33 highlighting effects on flight hour supply enforces the previous statements. An increase of maintenance capacity of at least 50% is indicated. The recommendations given in Section D of this Chapter will shed more light on the final statements. This increase in capacity necessarily requires more personnel, infrastructure, and equipment at levels that cannot be quantified within the scope of our study.

An inspection module that covers personnel requirements and flow of spare parts, as well as aircraft key equipment such as calendar-based maintenance items like engines or gear boxes, could be integrated into the existing model to achieve further insight into resourcing requirements. This is discussed in more detail in Section D of this chapter.



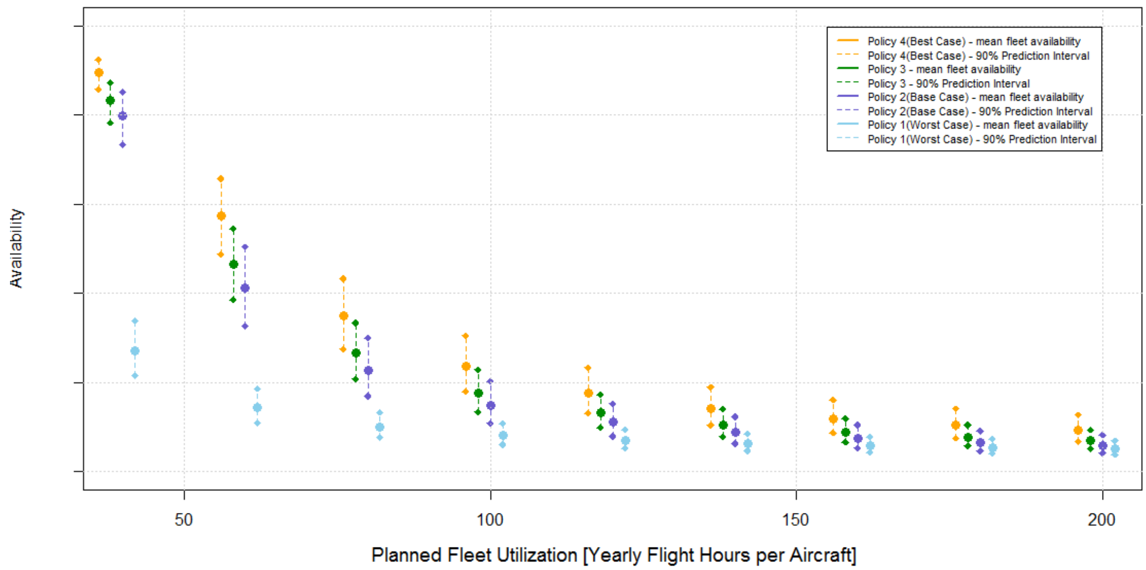
Single point time series results shown present bank time as function of time for Inspection Duration variants relative to base case - alpha: -30%, bravo: -40%, Charlie: -60%, delta: -70% and changes in maintenance capacity.

Figure 33. Flight Hour Supply over Time for different Inspection Turnaround times of major usage-based inspections at 80 Yearly Flight Hours per Aircraft and MTBF Improved by a Multiplicative Factor of 2

C. ADDITIONAL RESULTS

1. Comparison of Maintenance Policies

Four maintenance policies are compared in the study, representing different mixes of usage- and calendar-based inspections (see Chapter I, Section C., para. 4). Simulation results for availability rate as function of planned fleet utilization is presented in Figure 34.



This plot shows simulated outcome for fleet availability rate in % over fleet utilization in flight hours per aircraft and year for all maintenance policy options studied. Results shown include mean and 90% prediction interval for availability rate derived by utilizing the *predict*- function in *R*.

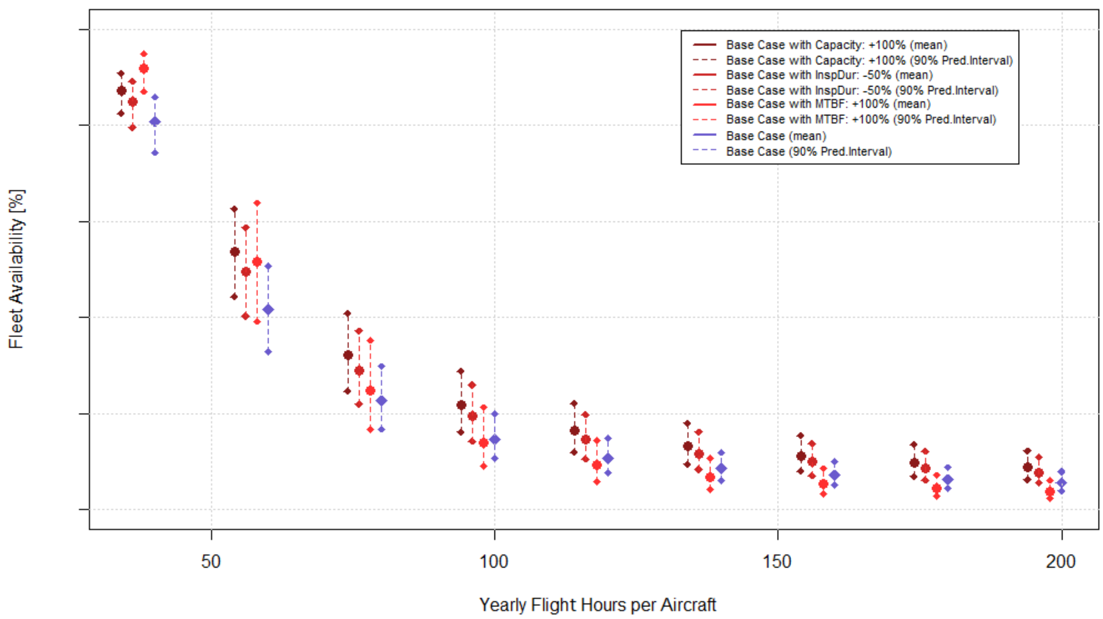
Figure 34. Fleet Availability as Function of Utilization with Four Maintenance Policy Options in Base Case Scenario

Option 1 became obsolete with the introduction of maintenance policy option 2 on 1 April 2016. Nevertheless, this option is included in the study for comparison purposes and to quantify the impact of the historical management decision representing the switch from policy 1 to policy 2. Again, option 2 or maintenance policy 2 constitutes the inspection system for the base case scenario for this study.

Figure 34 presents the results for comparison of the four maintenance policies under base case conditions. With respect to the results shown, canceling policy option 1 was obviously a good decision. It performs significantly worse than all the others. Further comparison of option 1 design combinations (results not presented), including actual factor improvements, could not outperform the base case scenario. All options have a non-linear declining trend with respect to increasing fleet utilization in common, which could already be observed for the base case scenario. Although the advantage is declining with increase in fleet utilization, by comparing the different maintenance options, non-negligible differences in fleet availability can be observed. Also, options 3 and 4 seem to dominate the base case scenario including option two. Augmented with other measures, a change in maintenance policy could result in significant improvements in performance.

2. Maximizing Return on Investment

To find out which factor has the most significant influence on fleet availability, the following isolated modifications are evaluated in direct comparison with the base case scenario by using the NOB metamodel results and maintenance policy 2, after changing the hard-coded MTBF parameter to the original MTBF×2. Plots are provided showing inspection turnaround time -50%, and Maintenance Capacity×2. Figure 35 shows the results of this analysis.



NOB simulation results shown represent isolated factor changes in inspection duration, capacity and aircraft reliability (MTBF). All changes are either by factor 2 or ½ if applicable. This response-surface subspace represents a sensitivity analysis for comparison of factors.

Figure 35. Sensitivity Analysis of Factors MTBF, Inspection Turnaround Time, and Maintenance Capacity in Connection with Maintenance Policy 2

For this examination, maintenance capacity and MTBF are increased by factors of 2, and inspection duration is decreased to 50% of the base case level. Predictions should not be treated as precise values, but the metamodel still indicates the relative impact of the factors to improve or deteriorate the situation. From the perspective of isolated changes holding everything else constant, maintenance capacity has the biggest impact on fleet availability, inspection duration comes in second for yearly flight hours above 60, and MTBF has the lowest impact, especially for higher utilization rates. This effect was anticipated, because with this usage-based failure generation the number of failures increases with increase in usage. Also, an improvement in each measure on its own results in increased fleet availability in comparison with the base case, which is not surprising.

Despite our findings, assessing maintenance capacity on its own does not yield useful insights because existing aircraft docks are able to perform more inspections per year with declining turnaround times. Therefore, demand for aircraft docks might decrease with respect to given planned fleet utilization levels. The interaction between these two factors is important to investigate, which is done in the recommendations section in this chapter. Additionally, building up capacity is a time consuming, expensive business, which always yields the risk of unacceptably long dock idle times. Recall that some idleness is required for stochastic queuing systems, otherwise the expected queue length can go to infinity. Increasing maintenance capacity as a management option should always be considered in conjunction with other measures like a decrease in the time waiting for inspections to begin. Therefore, the primary focus for recommendations lies in finding an effective combination of both factors with parallel crosschecking of the average number of available (idle) docks.

3. Fleet Availability Rate as Function of Utilization

Figures 36 and 37 show the effects of maintenance capacity and inspection duration on fleet availability as functions of planned fleet utilization for different levels. The following metamodel results shown represent isolated changes in inspection duration. Inspection duration is decreased in contrast to base case level by the presented percentage while keeping everything else constant.

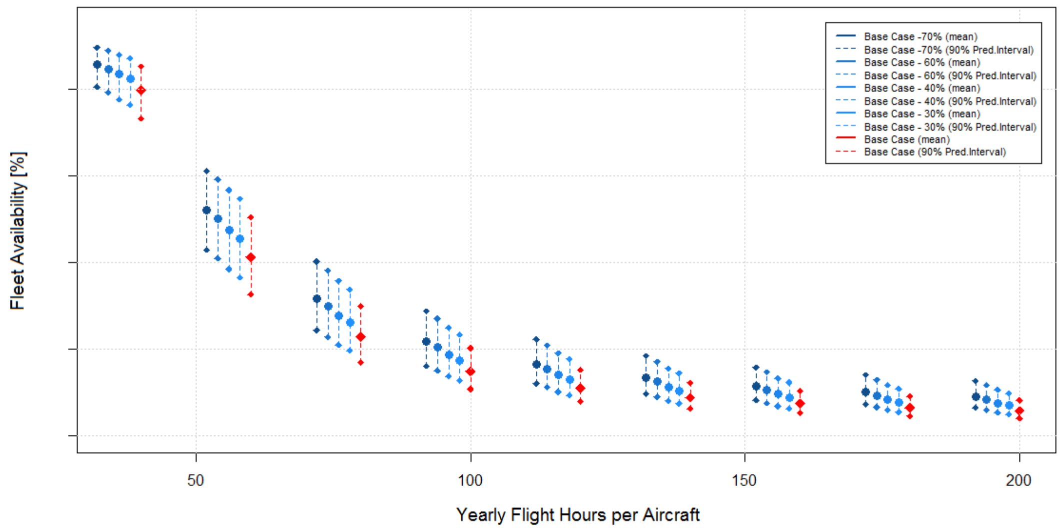
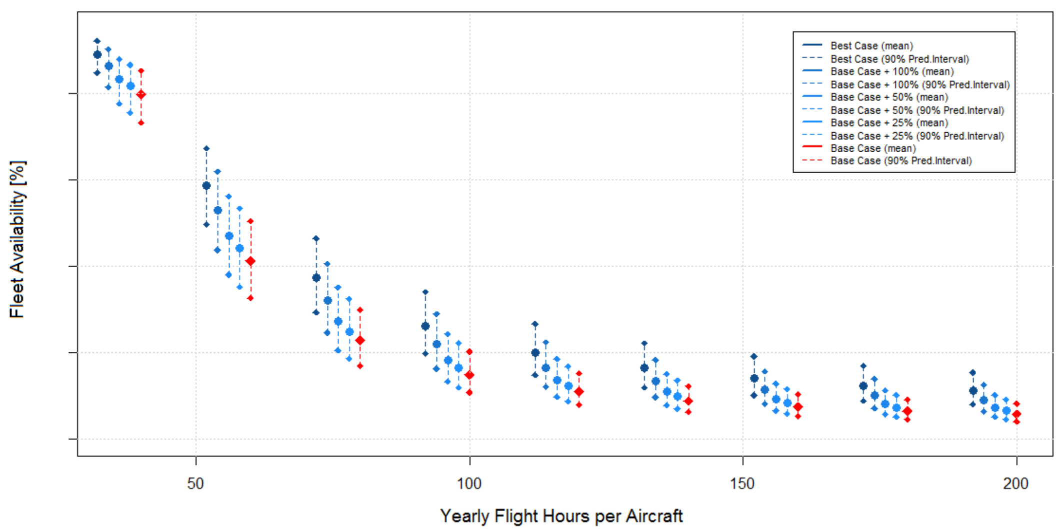


Figure 36. Fleet Availability over Yearly Flight Hours per Aircraft for Inspection Duration and Maintenance Capacity at Base Case Level

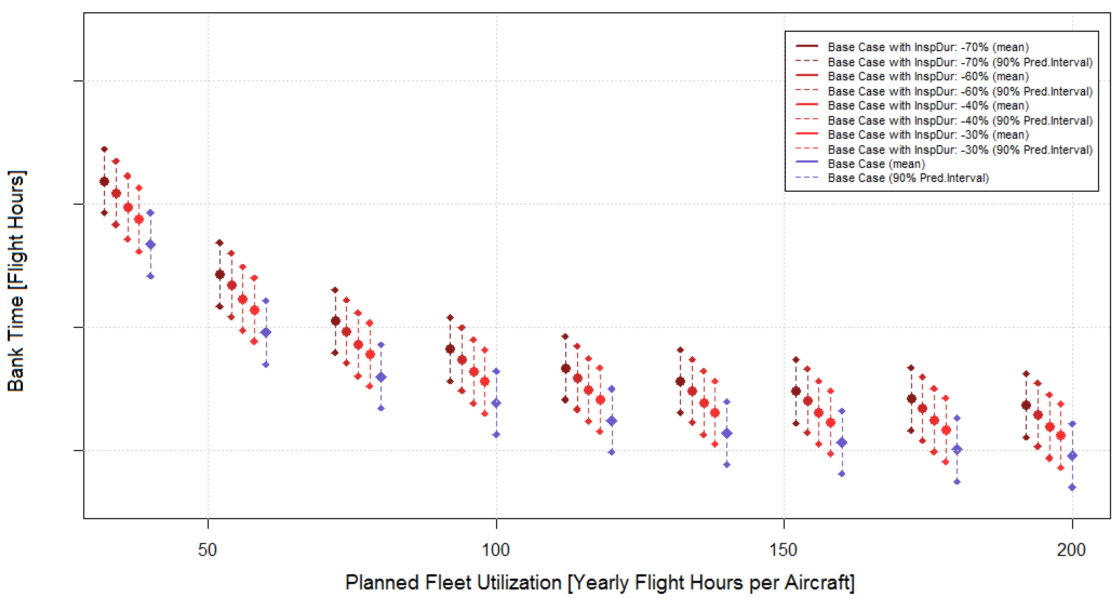


NOB metamodel results shown represent isolated changes in maintenance capacity. Capacity is increased in contrast to base case level by the presented percentage, while keeping everything else constant.

Figure 37. Fleet Availability over Yearly Flight Hours per Aircraft for Maintenance Capacity and Inspection Duration at Base Case Level

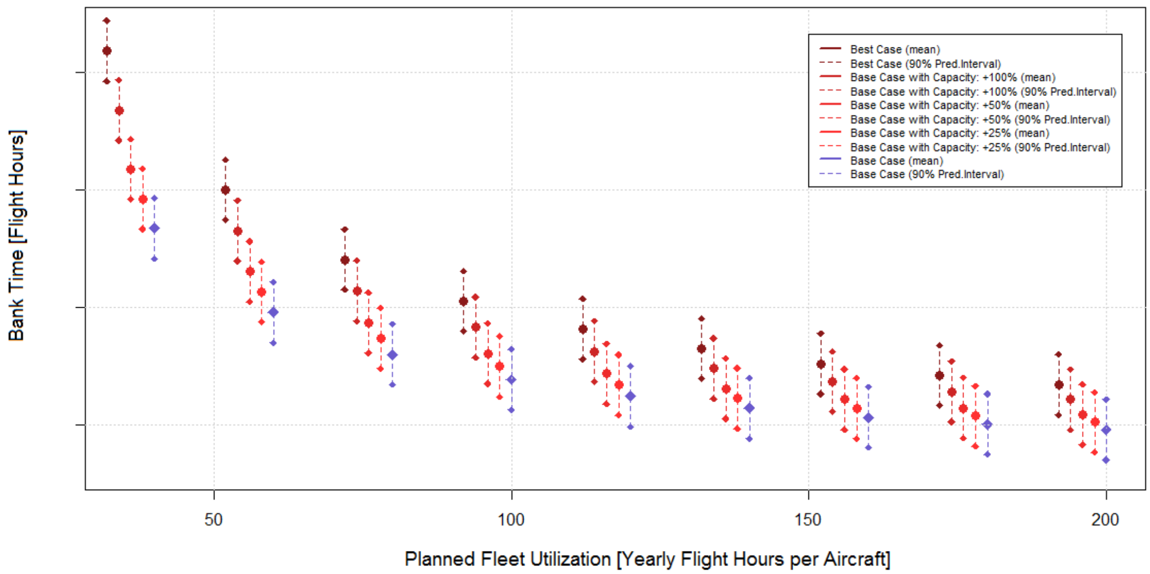
4. Flight Hour Supply as Function of Utilization

By examining Flight Hour Supply as a function of utilization shown in Figures 38 and 39, the same trends as in Figures 36 and 37 can be observed. Again, the base case scenario is outperformed by all alternatives evaluated, while maintenance capacity dominates inspection turnaround time throughout the whole interval. Both fleet availability and flight hour supply indicate changes are due in maintenance capacity and inspection turnaround time. Since a change in inspection turnaround time alone does not deliver satisfying results regarding the given daily aircraft availability threshold (see Figure 29), simultaneous changes in both factors are studied in section 6 of this chapter using the maintenance policy currently in practice. Results are compared and presented in terms of yearly distributions for deviation from threshold. To conclude this section, Figure 40 gives results for mission completion as function of utilization.



NOB simulation results for flight hour supply (bank time) shown represent isolated changes in inspection duration. Inspection duration is decreased from the base case level by the presented percentage while keeping everything else constant.

Figure 38. Flight Hour Supply as function of Planned Fleet Utilization for Inspection Duration—Option 2

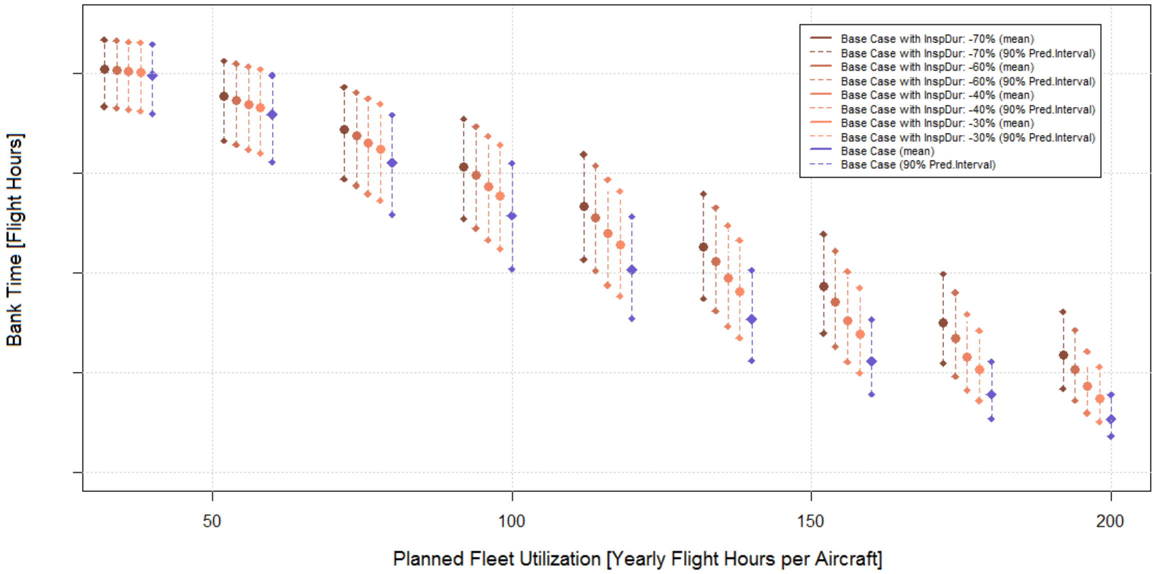


NOB simulation results for flight hour supply (bank time) shown represent isolated changes in maintenance capacity. Capacity is increased from the base case level by the presented percentage, while keeping everything else constant.

Figure 39. Flight Hour Supply as Function of Planned Fleet Utilization for Maintenance Capacity—Option 2

5. Mission Completion Rate as Function of Utilization

Figure 40 shows the impact of inspection duration on mission completion rate as a function of planned fleet utilization. Although improvements through reduction of inspection turnaround time are indicated, the negative trend with increasing planned utilization is observable. This effect is now shown to be present for all measures of effectiveness.



NOB simulation results for mission completion shown represent isolated changes in inspection duration. Inspection duration is decreased in contrast to base case level by the presented percentage while keeping everything else constant.

Figure 40. Mission Completion over Yearly Flight Hours per Aircraft for Inspection Duration—Option 2

D. RECOMMENDATIONS

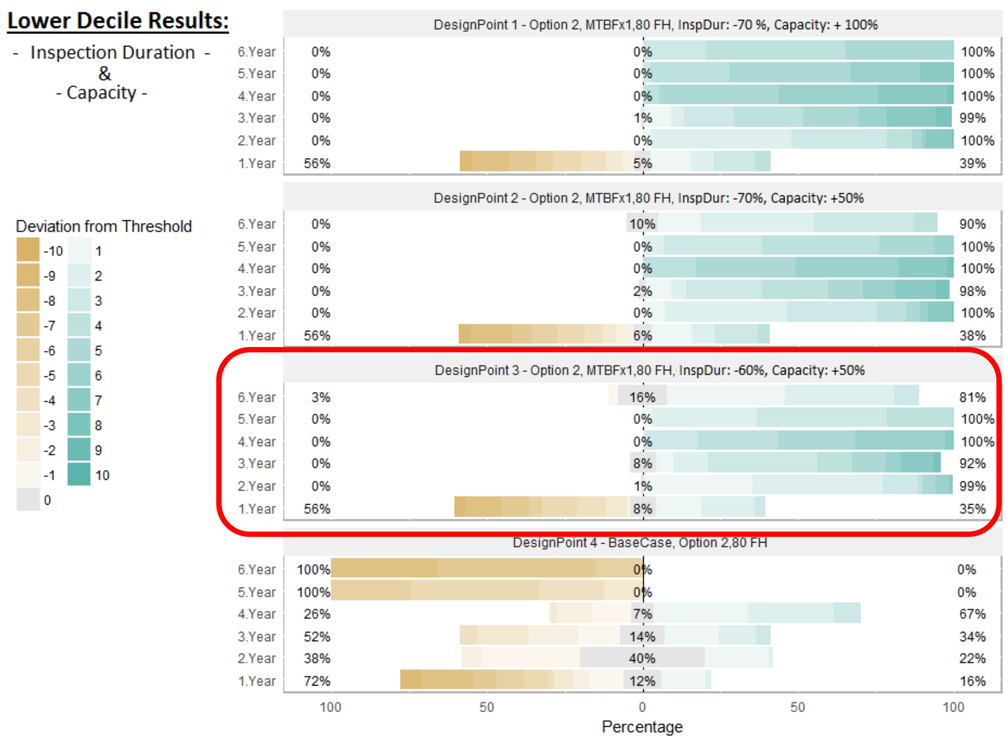
For development of suitable recommendations, different combinations of maintenance capacity and inspection turnaround times are evaluated at three levels of planned fleet utilization (at 80, 100 and 120 flight hours per aircraft and year). As a rule of thumb, maintenance capacity is selected as conservatively as possible to minimize the number of idle aircraft docks. Although changing any of the factors is not easy to do in practice and may also be expensive, inspection turnaround times are considered to be the best pick. As an example, according to the sponsor, the Australian Army is doing a remarkable job by performing the major inspections in just three months. As mentioned before, maintenance capacity and inspection turnaround times always should be evaluated together. After narrowing down factor combinations for these two factors, the remaining three maintenance policy options 2, 3, and 4—which represent different inspection systems—are studied under the given scenarios. Finally, reliability is altered by evaluating mean time to failure at three different multiples of the baseline (2, 2.25, and 2.5), if previous changes are not sufficient to reach given margins. Although each individual aircraft has a defined reliability derived from live fleet data, it can be influenced by applying technical measures such as software updates or improvement of components.

The factor settings were chosen after considering the earlier results, and discussions with the sponsor about what changes to reliability are of interest to study. New runs are required because the MTBF was not included as a factor in the initial study. It is varied at just a few levels because it is currently hard-coded into the simulation model and cannot be easily manipulated. The results that follow could have been estimated using metamodels, as in earlier studies, but a different approach was taken. Confirmation runs of the simulation were created, by generating 30 replications of the selected factor combinations, to ensure that the improvements associated with the final recommendations due not suffer from any lack-of-fit of the metamodel.

1. Rough Estimation via Threshold

Figure 41 contrasts evaluated factor combinations for maintenance capacity and inspection duration against the base case scenario at the 80 FH level. Results presented show a significant improvement in the number of daily available aircraft throughout the years. While reducing the proportion of days with threshold violations in the first year, nearly all other years are at or above the threshold close to 100% of the time. The first year is primarily determined by fleet condition at $\mathbf{t_0}$ which includes important properties of the aircraft given by fleet data. Therefore, differences shown for 2015 are of little interest.

Given the current reliability of aircraft in the fleet and failure repair times, simulation results presented in Figure 41 imply that at 90% of days in years two to six, a reduction of inspection turnaround time of 60% with a simultaneous increase in maintenance capacity of 50% is sufficient to meet the given threshold of daily aircraft availability. This investment produces a substantial improvement in the number of aircraft available for flight missions on a daily basis and reduces the proportion of days simulated with threshold violations by 64% (from 74.7% to 27%). This means that on average there is a 90% chance that on 73% of all days in the six-year period, the given threshold of 10 aircraft is met or exceeded. Although daily availability of aircraft could be improved further by choosing a more rigid combination with even lower inspection duration, this conservative result is carried on, due to significant efforts that have to be done to achieve these levels.



This Likert plot shows lower decile for number of aircraft serviceable for flight missions normalized on the given threshold of 10 aircraft, which is represented by the zero – line dividing both sides in the plots. Brown is below, grey exactly at and blue above threshold. Shading represents the actual differences according to the given legend.

Figure 41. Yearly Distributions for Deviation from Threshold of Daily Available Aircraft Covering Presented Design Points at 80 Flight Hours per Aircraft and Year

Figure 42 shows results for 100 flight hours per aircraft and year. Since the availability gap or deviation from the threshold of number of daily available aircraft as an MOE is derived from the availability rate, similar conclusions arise. The highlighted results are considered as recommendations for further review, since fleet availability alone is not enough to make conclusions about overall performance of recommended adjustments. In particular, dock utilization as an MOE has to be cross-checked to ensure that utilization of maintenance capacity is sufficiently high to warrant the additional cost, while not so high that maintenance queues build up and availability suffers.

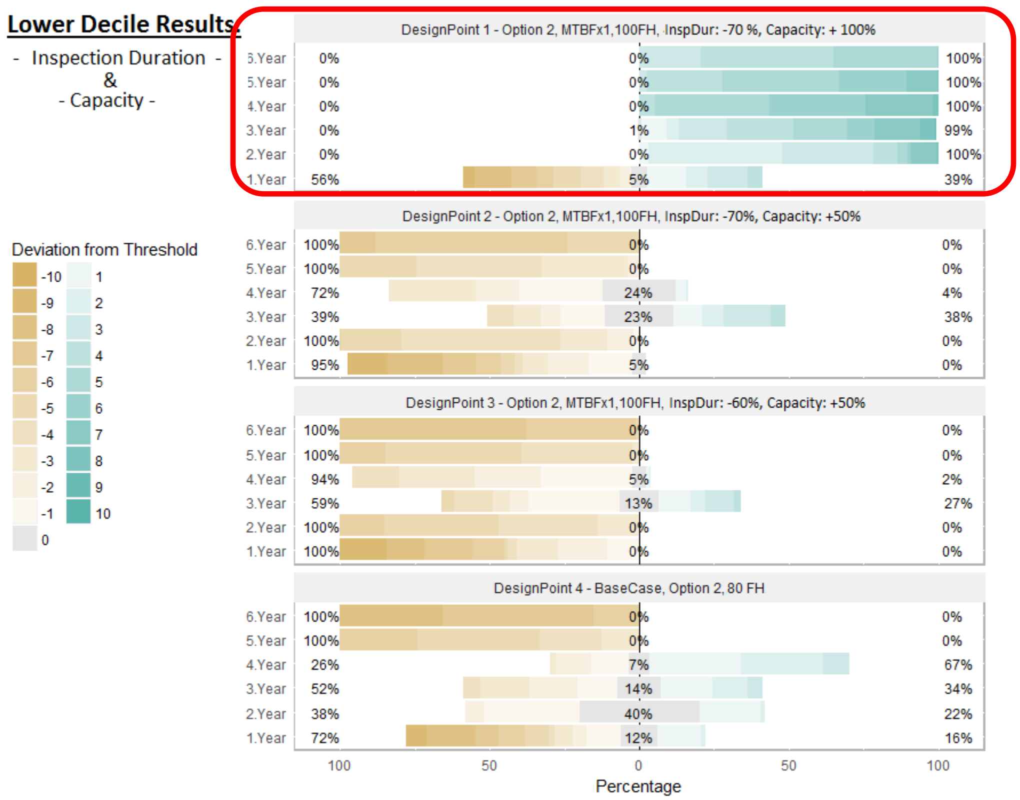


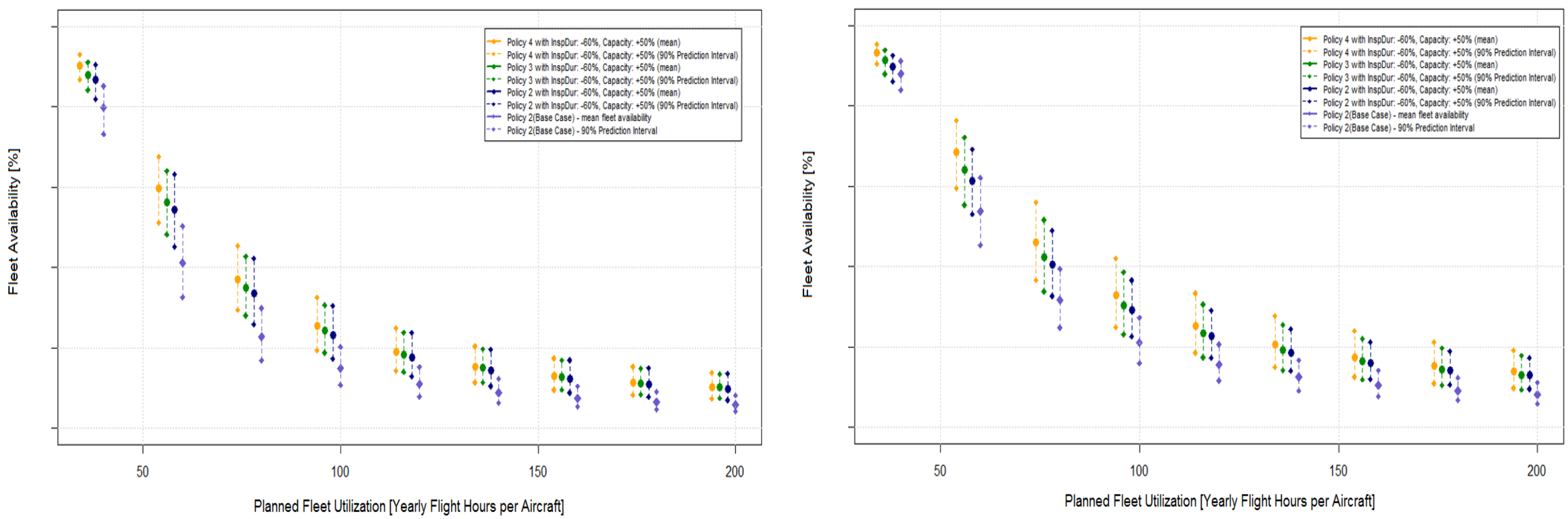
Figure 42. Yearly Distributions for Availability Gap Covering Presented Design Points at 100 Flight Hours per Aircraft and Year

From Figure 42, it is clear that an increase in maintenance capacity of 50% alone is not sufficient to ensure that the daily availability threshold criterion of 10 aircraft is met throughout the simulated time line. Because the reduction of inspection duration to its feasible lower bound (-70%) at the level of a 50% improvement in capacity does not result in significant improvement of the number of available aircraft per day, a 100% increase in capacity is indicated. This level represents a doubling in the number of available aircraft docks.

To develop finalized recommendations from these estimates, the indicated factor combinations are analyzed with respect to MOE availability rate and mission completion rate for the three remaining maintenance policies as functions of planned fleet utilization to localize prioritized estimates. Finally, the refined results are cross-checked with respect to dock utilization to ensure reasonable and realistic results.

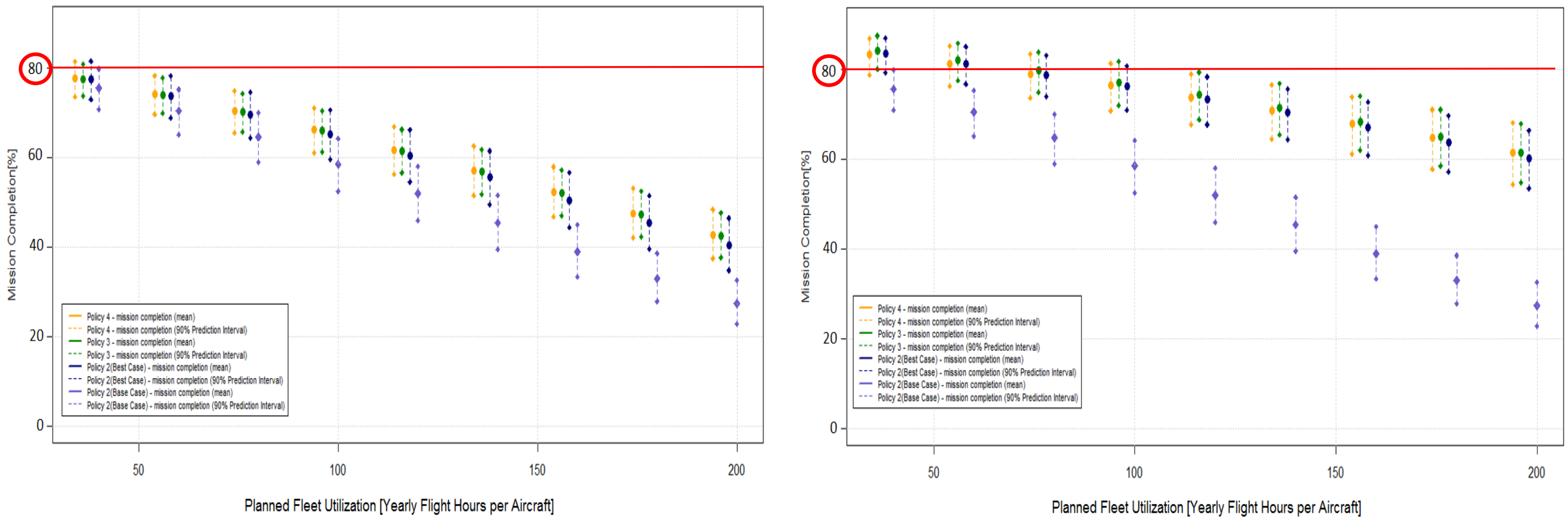
2. Localization of Prioritized Estimates

Results for the prioritized factor combination at 80FH level (-60% in inspection duration and +50% in capacity), in combination with remaining maintenance policies presented in Figures 43 and 44, show a significant improvement in comparison with the base case (slate blue), but only insignificant differences between policies, especially for mission completion. Changing the maintenance policy is an extensive measure that always bears the risk of negative effects on inspection turnaround times, which would outweigh the small advantage in performance especially for higher fleet utilization levels.



Presented NOB results show availability as function of planned fleet utilization in yearly flight hours per aircraft for the three remaining maintenance policy options 2, 3 and 4.

Figure 43. Estimate for Recommendation at 80 FH, All Options with Inspection Duration – 60% and Capacity + 50%, MTBFx1 (left) and MTBFx2 (right) for Availability Rate



Presented NOB results show availability as function of planned fleet utilization in yearly flight hours per aircraft for the three remaining maintenance policy options 2, 3 and 4.

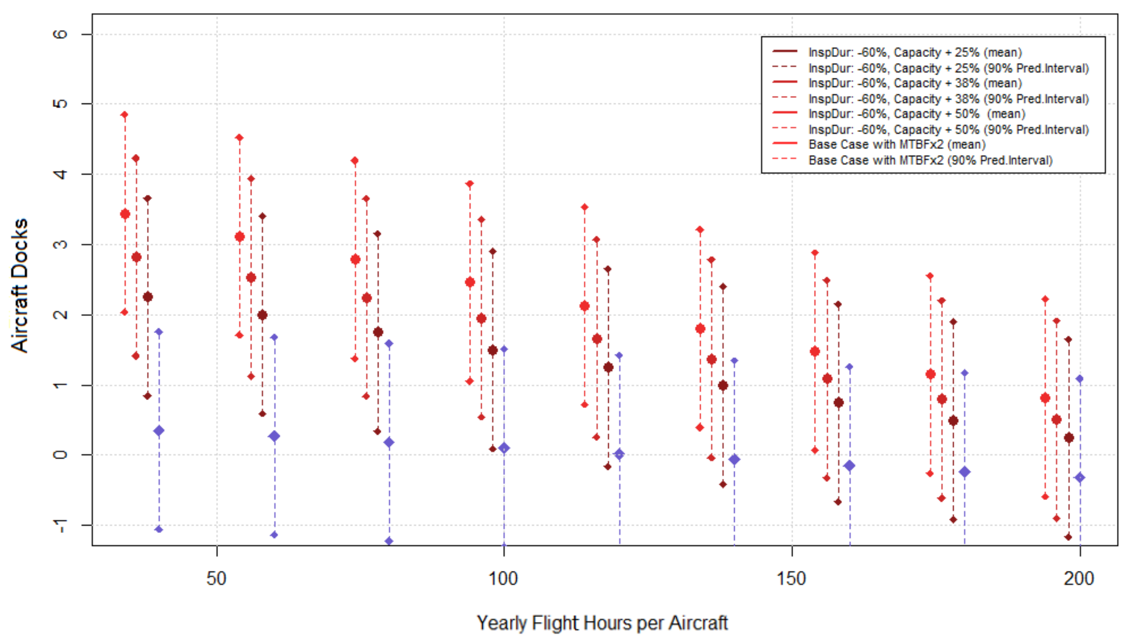
Figure 44. Estimate for Recommendation at 80 FH, all Options with Inspection Duration – 60% and Capacity + 50%, MTBFx1 (left) and MTBFx2 (right) for Mission Completion Rate

Therefore, maintenance policy option 2 (dark blue) is prioritized, to avoid the risk of increasing turnaround times. While comparing given results for availability and mission completion rates at the original level of aircraft reliability on the left and doubled MTBF on the right, the global improvement for fleet performance is obvious. By increasing MTBF by a factor of two, overall improvements of about 4–6% for fleet availability rate and roughly 10% for mission completion rate can be observed at the 80, 100, and 120 FH levels for the presented recommendation. Although this is a hypothetical view on fleet condition with respect to reliability, this is a useful insight with implications for future requirements of aircraft reliability. Changing aircraft reliability is hard to achieve, but possible with respect to software updates, improvement in reliability of components, and additional spare parts. Results for mission completion rate in Figure 44, in particular, reveal that improvement in aircraft reliability is vital to achieve the desired completion level of 80%, since the shortfall at the 80 FH level still is evaluated at about 9% with the original MTBF values. This effect is even more significant at higher fleet utilization levels, although improvements in contrast to the base case are observable.

3. Cross-Checking Dock Utilization

With reference to Figure 45, the impact of an increase in number of aircraft docks becomes clear. On average, at least one dock is found to be in idle state for all levels of utilization, while the base case shows no slack. Zero slack in dock capacity is always a sign of an unstable system in queueing theory, which means results indicate insufficient maintenance capacity for the base case, resulting in an increasing queue length over time. This effect is already shown in Figure 21. Having a ratio between queue length and average number of idle docks less than 0.8, such that there are 20% more idle docks than number of aircraft waiting for inspection entry, is said to indicate a stable system. Ratios between 0.8 and 1 are already indicating insufficient server capacity through increasing queue lengths.

With respect to the recommended option including a 50% increase of maintenance capacity, two to three docks are idling on average. Although having idle servers is in line with queueing theory, this level of capacity may be too optimistic. Although no information about possibly imminent queue length is given so far, a 25% increase in capacity seems to be sufficient at the 80 and 100 FH levels, while 38% seems to be a good fit for a fleet utilization of 120 FH per aircraft and year. The previous statement is based on moderate slack in maintenance capacity utilization of about 1.5 idle aircraft docks on average. The question remains whether these factor changes will satisfy the sponsor-given availability and mission completion criteria.



NOB simulation results present estimated mean number of idle aircraft docks as function of planned fleet utilization. Maintenance capacity is increased in contrast to base case level by the presented percentage while keeping everything else constant.

Figure 45. Dock Utilization for Different Maintenance Capacity Levels as Function of Fleet Utilization—Option 2

To get a better understanding of utilization of maintenance capacity from simulated outcomes for recommendations, the ratio between the average queue length and the average number of idle aircraft docks is evaluated. We call this AQ/AD. Examination of different queueing techniques is not a part of this study and is subject to future work.

4. Summary of Final Results

The previously considered changes to inspection duration (-60%, -70%) with simultaneous changes in maintenance capacity (range: +25% to +50%) are now examined for each planned fleet utilization level of interest. All measures of effectiveness are examined including average number of idle aircraft docks and additionally the average number of aircraft waiting for inspection entry in order to determine maintenance system stability (Table 4).

Table 4. Sensitivity Analysis Summary for Recommendations at Three Levels of Fleet Utilization (80,100,120 FH)

Factor Combination				Mean Response (1000 Replications)					
YFP.AC	**InspDur**	**Capacity**	**MTBF**	**InQ**	**IdleDocks**	**ARate**	**THD**	**MC**	**FHS**
@ 80 FH	BaseCase	BaseCase	x1	2.6	0	Benchmark	Benchmark	Benchmark	Benchmark
@ 80 FH	-60%	25%	x1	1	1.5	+7.7%	+186%	+6.4%	+34%
@ 80 FH	-60%	50%	x1	0.6	2.8	+8.5%	+201%	+6.4%	+37.4%
@ 80 FH	-60%	25%	x2	0.5	1.7	+17.5	+339%	+13.9%	+40.1%
@ 100 FH	BaseCase	BaseCase	x1	8	0	Benchmark	Benchmark	Benchmark	Benchmark
@ 100 FH	-60%	50%	x1	1.5	2.0	+8.9%	+627%	+10.6%	+41.4%
@ 100 FH	-60%	50%	x2.25	0.5	2.5	+21.1%	+1235%	+20.4%	+50.2%
@ 100 FH	-70%	25%	x2.25	0.9	1.9	+22.9%	+1200%	+20.2%	+53.8%
@ 120 FH	BaseCase	BaseCase	x1	10	0	Benchmark	Benchmark	Benchmark	Benchmark
@ 120 FH	-70%	50%	x1	2.2	2.2	+8.5%	+661%	+13.3%	+50.7%
@ 120 FH	-70%	50%	x2	1.4	2.5	+17.6%	+1061%	+25.2%	+55.1%
@ 120 FH	-70%	38%	x2.5	1.4	2.0	+20.1%	+1190%	+26.4%	+55.6%

InQ = Number of Aircraft waiting for inspection entry, ARate = Availability Rate, THD = Threshold deviation in number of daily serviceable aircraft, MC = Mission Completion rate, FHS = Flight Hour Supply.

In cases in which satisfaction of the given mission completion rate threshold of 80 % could not be ensured, different levels of aircraft reliability were evaluated, too.

Although fleet condition is determined by the data provided, it reveals that there exists no state of fleet performance that satisfies the given constraints regarding all MOEs without significantly improving aircraft reliability as a factor that drives fleet dynamics. Of all the MOEs, an 80% level of mission completion is the hardest to achieve. Table 4 summarizes all results covering the three utilization levels that are considered in the study. Resulting recommendations for each level are derived by evaluating all four MOEs and simultaneously taking queue length into account. Also, different levels of average aircraft reliability are taken into account where appropriate. In our analysis, the upper bound for increased maintenance capacity is taken to be +50% and the lower bound for major inspection turnaround times is taken to be -70%. These bounds are a result of consultations with subject-matter experts in the German Army.

5. Recommendations

Although a significant improvement in fleet availability and flight hour supply could be achieved with the factor combinations corresponding to each of the confirmation runs in this section, the given mission completion constraint of 80% could only be achieved with a substantial improvement of aircraft reliability. This improvement is determined by an average increase of MTBF of at least a factor of 2 across the entire fleet. A recommendation at the current MTBF level is possible for a utilization of 80 FH and 100 FH, but only by accepting a substantial reduction in mission completion rate. This is not the case for 120 FH: to achieve a sustainable fleet performance at 120 FH (120 x 53 = 6,360 FH in total for the fleet) requires improvement in aircraft reliability, as well as improvements in inspection duration and dock capacity. In addition, there is a trade-off between availability and the number of idle aircraft docks. The detailed recommendations are presented in Table 5.

Table 5. Summary of Recommendations

Scenario	**Change in Policy**			**Results of Change**				
	Duration	**Capacity**	**MTBF**	**AQ/AD**	**AR**	**THD**	**MC**	**FHS**
80 FH	-60%	+25%	1.0	0.67	+7.7%	x 1.9	- 9%	+34%
100 FH	-60%	+50%	1.0	0.75	+8.9%	x 6.3	-11%	+41%
120 FH	-70%	+38%	2.5	0.75	+20%	x 11.9	80%	+56%

This table summarizes results simulated outcome for recommendations including all measures of effectiveness used in this thesis, availability rate (AR), threshold deviation or availability gap (THD), mission completion rate (MC) and flight hour supply (FHS) plus the AQ/AD ratio.

V. CONCLUSION AND OUTLOOK

A. SUMMARY

The objectives of this study are to develop and exercise a simulation-based model of the German TIGER aircraft fleet. Our model quantifies the effects of several factors on fleet availability, flight hour supply, and mission completion. Although not all possible factors could be incorporated into the model due to time constraints, we show that our model is able to accurately reconstruct the recent condition of the fleet.

1. General Benefit

The general benefit of this work is not only the logistic TIGER fleet model and analysis results that were achieved, but also the insight gained into the actual fleet data following extended discussions with the sponsor about the interpretation and practical implications of the study results. Results from the analysis presented here offer insight on the future state of the fleet conditioned on actions that are taken to improve its performance. Estimated aircraft failure-time probability distributions give insight on reliability of aircraft, which is a practical aid for mission planning. This technique, applied to aircraft equipment and components, can be used to set inventory and maintenance policies, compare different maintenance policies, identify reasons for performance shortfalls, and estimate the expected number of aircraft available daily for flight missions.

2. About the Model

The final model structure is easily adaptable to include future fleet parameter changes, in- and outflow of aircraft, and to incorporate other aircraft types. However, given the mathematically intense processing for visualization in *R* and the lack of a graphical user interface, it will require adequately trained personnel in order to realize the full potential of this technique. The model itself works stably for the subset of input design space studied and it shows reasonable accuracy in predicting outcomes, with a mean error of about 4.3% for the validation time period 1 April 2015 to 31 December 2016. Although a range of explanatory variables are considered, the current version of the model excludes personnel requirements, key equipment, and spare parts with their corresponding categories. Utilization of maintenance capacity can be added to the output, but queueing protocols are not currently included in the model.

B. CONCLUSIONS

1. Base Case Analysis

The motivation for the study is to examine the worsening of aircraft availability if current usage of the German Army aircraft fleet is continued as-is, which constitutes the base-case scenario. Model validation reproduces this trend, and the study shows how changes to fleet resourcing and management can be expected to affect it.

a. Fleet Availability

Fleet availability is projected to stay at a consistently low level around current values during the whole simulated period unless corrective measures are adopted. Negative impacts are projected to manifest in later years, especially in 2019 and 2020. The two ways to increase long term availability under the current circumstances are to reduce utilization or grow the fleet size.

b. Flight Hour Supply

Flight hour supply curvature develops a global maximum around the time that the aircraft delivery phase ends. After that it starts to degrade with a relatively constant negative slope. Flight hours are consumed faster than they can be replenished. As a result, fleet performance degrades. Although the various scenarios considered in the study are quantitatively different, the same pattern holds for each.

c. Mission Completion

Mission completion averages to about 60% for the base case, but that average contains a decline at a constant slope of -10% for each flight-hour increase of 20 hours per aircraft per year. Mission completion at target flight-hour levels (120 FH) on average drops to 40%, which is only half of the desired target level.

d. Bottom Line

Although the management decision to change the maintenance policy from *option 1* to *option 2* on 1 April 2016 shows significant positive effects, additional enhancements are still needed to achieve sustainable fleet performance.

2. Recommendations

Upon reviewing all results from our study, option 2 performs best overall. Specific findings are outlined below:

a. Utilization of 80 Yearly Flight Hours per Aircraft

Improving turnaround times for major inspections alone does not reverse the negative trend in fleet availability and flight hour supply. Also, it does not keep the daily number of available aircraft from falling below the target threshold a significant proportion of the time, especially in years five and six. Given existing failure repair time distribution, aircraft reliability, special inspection probability threshold, and minor inspection turnaround times, a significant improvement can be achieved by simultaneously decreasing major usage-based inspection turnaround times by 60% and increasing maintenance capacity about 25%. Simulation results predict threshold violations to be at only 3% by the sixth year. Despite poor outcomes in the first year, which is anchored by the current fleet status, the rest of the simulated period is predicted to have a sustainable availability of aircraft. On average, fleet availability is estimated to improve about

9% over the simulated period. Also, mission completion, although 9% below the target given by the sponsor, on average increases by about 6.4%.

Because building maintenance capacity, especially in the military environment, is a time-consuming and expensive undertaking, expanding capacity to a certain degree requires careful consideration. A 25% increase in capacity combined with a 60% decrease of inspection turnaround time, while keeping inspection queue and dock idle times in balance, would be sufficient to achieved desired goals.

b. Utilization of 100 Yearly Flight Hours per Aircraft

Our recommendation for utilization at 80 flight hours per year does not perform satisfactorily at 100 flight hours with respect to fleet availability and mission completion, unless maintenance capacity is increased while keeping inspection turnaround times at the same level. To keep inspection queue length and idling dock capacity in balance, no more than a 50% increase in capacity is recommended. With this recommendation, fleet availability is estimated to improve about 9%. While mission completion is predicted to remain 11% below threshold, it can be improved by 10.6% relative to the situation without changes in aircraft reliability. If aircraft reliability, expressed by the mean time between failures (MTBF), can be improved by a multiplicative factor of 2.25, then the mission completion threshold level is achievable while improving fleet availability by about 23%. It is not clear, however, how an improvement of this magnitude can be achieved or even if it is physically achievable. However, direct conversations with the sponsor indicate that they believe improvement is possible, and they intend to pursue this goal.

c. Utilization of 120 Yearly Flight Hours per Aircraft

A sustainable fleet performance that complies with all given thresholds and constraints would be achieved by reducing inspection turnaround times by 70%, the theoretical lower bound for the German TIGER fleet as defined by subject-matter experts, and by simultaneously increasing maintenance capacity about 50% and improving aircraft reliability (MTBF) by factor 2.5. These targets are based on the assumption that all other factors and parameters remain unchanged.

d. Impact on Management Practice

Despite acknowledging issues arising from the very young age of the TIGER fleet, preliminary results from this study have already been presented at integrated planning team meetings (IPT) with industry. A follow-on experiment is being planned to reveal weaknesses and to identify efficiency improvements in maintenance policies that may enhance future inspection performance.

Another use of our work is to quantify the impact of different maintenance policies on fleet performance. For example, the management decision to change the maintenance policy from *option 1* to *option 2*, effective since 1 April 2016, could be quantified to evaluate the effects of this decision. Similarly, *option 3* has been evaluated to show the impact of an alternative maintenance policy on fleet performance, especially with increasing utilization. Since *options 3* and *4* show inferior simulated fleet performance relative to *option 2*, these results can help management save time and money by avoiding an imminent risk of increased inspection turnaround times resulting from the proposed changes in policy.

The research question about placement of maintenance personnel could not be answered explicitly, but some insight can be gained. An extension of the model to include maintenance capacity is indicated, to yield recommendations for the appropriate aircraft dock crew sizes needed to properly operate the docks. We recommend allocation of workers in line maintenance as a subject for future work.

C. FUTURE WORK

1. Queueing Protocols

Currently the management of fleet data is handled using a *Python* dictionary data type, which follows management rules of hash tables. Hence, the fleet object containing all the aircraft is not sortable. When there are aircraft waiting for major maintenance inspection in the fleet and dock space becomes available, the first aircraft encountered in the unordered dictionary that matches the inspection-due criteria will be chosen for inspection, no matter how long it has been waiting so far.

Given the complete lack of ordering, the inspection assignment is *de facto* random. It is possible that a specific aircraft might never start its inspection within the time frame being simulated. Since individual aircraft are not the focus of this study, the order of inspection has been assumed to be negligible with respect to overall fleet availability, but this deviates from the assignment methodology used in practice. The model implementation might have some effect on the flight hour supply of the fleet as an MOE. Performing calendar-based inspection does not produce flight hours, since the usage calendar will not be renewed. Hence, due to prioritization, fewer flight hours will be reproduced for the fleet, and flight hour supply is increasingly degraded over time. The FIFO principle maps actual operations better, without distinguishing between types of inspection—only the time stamp counts. While FIFO would be a better fit for current practices, the model used for this study is predicated on the hash table's native behavior, and effects on waiting times and prioritization of aircraft for maintenance are treated as negligible. However, the queue length and number of idle docks are tracked and reported for analysis, and could be examined in more detail. Future model development should include explicit queuing protocols in order to deal with heavy fleet utilization or mission deployment scenarios. Very high operational readiness requirements might dictate prioritization of certain aircraft over others under a given set of conditions in that case. Another alternative might be to service shortest processing times first. Due to time constraints for this study, the evaluation of different queuing protocols is a subject for future work.

2. Aircraft Assignment Algorithm

The aircraft assignment algorithm is constructed to reflect subject-matter-expert opinion. Aircraft assignment is driven by a monthly updated utilization budget with respect to flight hours remaining until the next inspection is due. In practice, this updating process is done on a daily basis, which also takes special events such as large exercises into account. The assignment algorithm can be improved by allowing multiple assignment policies to be evaluated concurrently. This could include reliability-driven or dock-utilization driven aircraft assignment with daily utilization updates. By incorporating failure probabilities and residual TBF values, or the expected number of days until maintenance capacity becomes available, a defined utilization of individual aircraft could be implemented, which might influence fleet performance.

3. Key Equipment and Personnel Module

The helicopter system spans several major groups of equipment that require different fields of expertise for maintenance. Instead of focusing on reliability and inspection system of the entire aircraft, the aircraft object in the simulation model could be implemented with its key equipment as a subset of material that is modeled by tracking component-level properties, maintenance policies, and flight safety constraints. The aircraft then would have particular causes of failure that require a defined mix of expertise, man hours and special spare parts, any of which might be unavailable. The same methodology would apply to inspections. With this methodology, the number of maintainers in both line maintenance and deep level maintenance could be studied using simulation, which would answer the question of personnel and equipment demand. However, this approach would involve greater complexity since it would require additional fleet data such as number of personnel work hours or maintainers of each specialty field needed for each maintenance action, as well as the number currently available for work. This modeling problem could represent a new research project in its own right.

4. Inventory Policy Module

Inspections or other maintenance tasks like failure repair often are delayed due to missing spare parts. This could have many causes, including long production lead times, obsolescence, or simply the applied inventory policy. By using an equipment and spare part reliability model, demand for spare parts could be generated and served by an inventory module, which would require modeling of key equipment. This module could account for demand in key spare parts and aircraft main equipment, which has the potential to improve fleet availability as well as mission completion and flight hour supply.

5. Inspection Module

In our model, the inspection durations are given by inputs that are assigned fixed values for every aircraft and every inspection. Alternately, an inspection module could generate this number by simulating the network of maintenance tasks with the corresponding probabilities of delay due to several new input factors, which drive inspection turnaround times, such as spare parts inventory, available maintenance personnel, misconduct, and many more. Using this module, inspection duration itself could be optimized through simulation. Such a model does not necessarily need to be implemented in the fleet model—it also could be deployed in a stand-alone approach.

6. Mission Deployment

Mission deployment is always stressful for humans, aircraft, and material. It has a huge impact on fleet performance due to availability constraints at the deployment location. Because resources such as personnel, key equipment, spare parts, and tools are limited, prioritization of maintenance tasks is most likely to cause impact on procedures at home. In addition, aircraft reliability might change due to the impact of extreme climate changes, saline environment, and events caused by operational usage. Also, battle damage repair and frequent air transport might influence availability and reliability of the aircraft. A mission deployment module could incorporate all these conditions and extend its capability to make predictions about the impact a possible mission deployment might have on fleet performance. This could be of particular interest if only a subset of the fleet consisting of a specific aircraft variant is capable of meeting mission requirements. To answer this research question, the properties of the aircraft objects would have to be extended along with changes in the model logic pertaining to new options. The impact of aircraft assignment for mission assignments at home and abroad, as well as different failure behavior and inspection needs, could be studied with a model modified in this fashion.

7. Model Updates Due to System Changes

All models are only as good as the data and the assumptions they are based on. Validity of model output will need to be re-evaluated as factors like aircraft reliability, failure repair times, or special event probability thresholds change over time. Therefore, input factors have to be monitored carefully and updated in the model from time to time. This should be done at least once per year, preferably twice.

8. Translation to Excel VBA

The only analysis resource in the standard work environment in the German Army besides SASPF is the Microsoft Office package, which includes *Microsoft Excel*. Since only IT specialists have administrative rights, open source software like *Python* or *R* is not available or is only available under certain circumstances requiring lots of paperwork and allowances. Therefore, this model should be translated into *Excel VBA* so as to be executable on all standard German Army computers. Although this work has already begun, finalizing it is part of the future work planning. *SimpleKit* methods, the aircraft object, and basic fleet functionalities are already up and running. However, so far it is unclear how the model can be ported without losing capability and performance, especially with respect to random variate generation and regression analysis. Having input parameters, model, and results in one Excel workbook is definitely an advantage that should be studied in the future.

9. Adaption to Other Weapon Systems

The model design is generic, which allows adaption to other aircraft types. The aircraft object, scheduling mechanism, factor data, and basic functionality can easily be adapted to accommodate different aircraft types. Adaptation of the maintenance system, however, may be more difficult due to the complexity of such systems. Therefore, this represents another potential future project for extending the existing model.

D. FINAL WORDS

An analysis approach using simulation to gain insight about the systemic behavior of an aircraft fleet has never been attempted within the German Army aviation forces before. Having an analysis tool that can be used on any standard computer and be used to produce meaningful assistance for quick-turnaround management decision-making is a huge step forward, especially given the complexity of the aircraft and the guideline, procedural, and technology constraints that fleet managers must confront. The German Army now has the capability to make the most out of its operational fleet data. If maintained properly, the model’s flexible architecture is adaptable to any kind of system changes in the future, and can incorporate other flying weapon systems. This thesis is the first exploration into uncharted waters, and should be considered as a guide for future analysis projects and further tool development to support fleet management.

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